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Review

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Review

A Systematic Review of Ship Wake Detection Methods in Satellite Imagery

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Abstract: The field of maritime surveillance is one of great strategical importance from the point of view of both civil and military applications. The growing availability of spaceborne imagery makes it a great tool for ship detection, especially when paired with information from the automatic identification system (AIS). However, small vessels can be challenging targets for spaceborne sensors without relatively high resolution. Moreover, when faced with non-cooperative targets, hull detection alone is insufficient for obtaining critical information like target speed and heading. The wakes generated by the movement of ships can be used to solve both of these issues. Several interesting solutions have been developed over the years, based on both traditional and learning-based methodologies. This review aims to provide the first thorough overview of ship wake detection solutions, highlighting the key ideas behind traditional applications, then covering more innovative applications based on deep learning (DL), to serve as a solid starting point for present and future researchers interested in the field.

Keywords: ship wakes; wake detection; maritime surveillance; multi-spectral; SAR; deep learning

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1. Introduction

Ship detection is a topic of great significance in the context of both civil and military applications, which stems from its utility in enhancing maritime security, safety, and environmental protection. A critical challenge for these systems is posed by "dark" ships, which are defined as vessels that do not broadcast their location or identification through the automatic identification system (AIS). AIS, despite being a pivotal tool for real-time maritime monitoring, is an opt-in system for most ships, with only vessels over 300 tons being required to keep broadcasting from their AIS transmitter [1]. This means that smaller vessels can deliberately turn off their AIS transmitter, making it difficult to track their movements. This creates a pressing need for alternative methods to monitor and detect ships, especially those engaged in illegal activities like smuggling, unauthorized fishing, and bypassing environmental regulations.

Moving ships generate a wake that can highlight their trajectory for tens of kilometers [2]. Theoretically, if one had a complete model of the wake characteristics and their generation mechanism, accompanied by full knowledge of significant local meteo-marine phenomena, the appearance of wake in remote sensing imagery could be used to discern not only the position of the vessel, but also its size, velocity, and heading [3–5]. This is because the features of the wake of a ship are highly dependent on the previously listed variables [2]. Furthermore, ship detection from spaceborne remote sensing is intrinsically limited by the resolution of the sensors, which greatly reduces the potential for detection of small vessels. In this sense, wake detection provides another avenue for small ship detection, since some structures of the wake offer significantly larger features than the hull itself.

Thus, the field of ship wake detection has attracted a wide range of researchers and practitioners from various disciplines, including remote sensing, maritime surveillance, environmental science, and computer science. This interdisciplinary interest underscores the complexity and importance of accurately detecting ships in different conditions and for various applications, and the utility that wake detection can offer for surveillance and security.

The methodologies for ship wake detection have evolved from traditional approaches to advanced deep learning (DL) techniques. The methods traditionally used to tackle the problem were based on the application of transforms like Radon and Hough, which served to highlight linear features in the imagery [6,7]. The transformed data would then be subjected to threshold-based techniques like constant false alarm rate (CFAR). Other approaches required manual feature extraction, following hierarchical paradigms involving the shape, texture, local binary pattern (LBP), and histogram of oriented gradients (HOG) [8]. With the development of DL in recent years, convolutional neural networks (CNNs) have seen an explosive rise in popularity for computer vision (CV) tasks requiring image-based feature extraction [9]. Initial experiments on the application of DL-based detection or segmentation models to the problem in question resulted in an improved detection accuracy of ships and their wakes in complex environmental conditions.

However, the most recent developments have involved the application of more task-specific DL models, which often include ideas from traditional approaches. One example of this is the inclusion of a Radon transform (RT) in the architecture of DL detection models [10]. One issue with DL-based applications is that they require large amounts of carefully curated data. For relatively niche applications such as wake detection, data availability can be an issue when it comes to training and testing the neural networks. Thus, most research on DL-based wake detection is accompanied by the development of relevant datasets. In some newer applications, the issue of scarce data has been offset by the use of synthetic data to augment existing datasets [11].

Li et al. [12] made a synthetic review of hull and wake detection, focusing specifically on the use of infrared bands in multi-spectral applications. However, many new applications have been reported, especially when considering the broader field of interest in both optical and radar applications. Moreover, both traditional and DL-based solutions have been proposed over the years, with a wide spectrum of ideas that have influenced the evolution of the field. Applications using both multi-spectral and synthetic aperture radar (SAR) spaceborne imagery are taken into account, with the objective of providing the reader with a thorough and complete review of the state of the field of wake detection in all its aspects. For that reason, this work can be effectively considered the first thorough overview of the field, and, hopefully, serve as a point of reference for future researchers interested in the topic.

The review is organized as follows:

- Section 2 provides an overview of the materials and methodology used while conducting the research and data gathering required for this review;
- Section 3 provides the results of the review. In particular, it first covers an overview of the characteristics of ship wakes, then moves onto traditional and state-of-the-art DL-based methods of ship wake detection;
- Section 4 contains a more high-level discussion of the field as a whole, as well as the challenges posed by ship wake detection, and the strengths and weaknesses of the state-of-the-art approaches. A meta-analysis is also provided in this section.
- Section 5 contains the conclusions of the review.

2. Materials and Methods

2.1. Literature Search Strategy

To conduct a comprehensive review of ship wake detection methods, a systematic literature search was performed across multiple academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, SPIE Digital Library, and Google Scholar. The search was conducted up to April 2024, to capture the most recent developments in the field. We used a combination of keywords and phrases related to ship wake detection and maritime surveillance. The primary search terms included: “ship wake detection”, “wake detection”, “maritime surveillance”, “synthetic aperture radar”, “SAR”, “optical imagery”, “multi-spectral”, “deep learning”, “machine learning”, “object detection”, “Radon transform”, “Kelvin wake”, and “ship wake characteristics.”

2.2. Inclusion and Exclusion Criteria

Specific inclusion criteria were established to select relevant studies for this review. Inclusion criteria included

- Studies that propose or evaluate methods for ship wake detection using remote sensing imagery, both SAR and optical.
- Research involving traditional and learning-based image processing techniques.
- Articles published in peer-reviewed journals or reputable conference proceedings.
- Publications in English.

Exclusion criteria were also established, which helped to outline the scope of this review and better interpret the meta-analysis presented in the subsequent sections. Exclusion criteria included

- Studies focusing solely on ship detection without considering wake detection.
- Papers dealing with wake detection in non-maritime contexts (e.g., aircraft wakes).
- Articles not available in full text.
- Non-peer-reviewed literature such as theses, dissertations, and white papers.
- Duplicate publications or extended versions of previously published works without significant new contributions.

2.3. Data Extraction and Synthesis

For each study that met the inclusion criteria, pertinent information was extracted. Firstly, publication details like authors, year of publication, and source were noted. The objectives and hypotheses of the study were extracted, together with the proposed methodology. The latter was the main focus of this work. Key findings and contributions were also noted, including improvements over previous methods.

Other information of note was the type of remote sensing data used by the authors, as well as any preprocessing techniques they applied. For datasets built to train DL models, their characteristics and those of their annotations were extracted. In terms of performance metrics, the wide variety of different metrics used for different data through different detection methodologies did not allow for a thorough comparison. While there are some widely accepted metrics for object detection (e.g., accuracy, precision, recall), these were most often not provided by the authors. Moreover, the provided metrics referred to the performance of their methods on different test data. As such, it was not deemed useful to conduct a value comparison.

The extracted information was organized into categories based on the type of detection method (traditional vs. DL) and image type (optical vs. SAR imagery).

2.4. Quality Assessment

To ensure the reliability and validity of the studies included in this review, a quality assessment was conducted based on the following criteria:

- Clarity and completeness of the methodological description, including data preprocessing steps, algorithm implementation details, and parameter settings.
- Adequacy of the experimental design, including the use of appropriate datasets, validation techniques (e.g., cross-validation), and statistical significance testing.
- Availability of datasets, code repositories, or detailed explanations that enable other researchers to replicate the study.
- The extent to which the study introduces novel approaches or significantly improves upon existing methods.

- Acknowledgment and discussion of any limitations, potential biases, or assumptions made in the study.

Studies that met most of these criteria were considered of higher quality and their findings were given more weight in the analysis. Any discrepancies or concerns about quality were noted and are discussed in the review.

2.5. Limitations

It is deemed important to note certain limitations of the review process:

- Only articles published in English were included, which may have excluded relevant studies in other languages.
- Despite using multiple databases, some relevant studies may have been missed due to the limitations of the search algorithms or restricted access.
- Given the fast-paced developments in DL and remote sensing technologies, some recent advancements may not be fully captured if they were published after our search had been completed.
- There is a possibility of publication bias, as studies reporting significant or positive results are more likely to be published.
- It would have been ideal to be able to reproduce and test the described methods on publicly available data. This, however, was not done for this review due to the inherent cost of such a thorough analysis.

These limitations were considered when interpreting the results, and efforts were made to mitigate their impact by cross-referencing citations and including studies from a range of sources and publication years.

3. Results

3.1. Overview of Ship Wake Characteristics

Although this report is not intended as a deep dive into the mechanisms behind wake formation, its modeling, or its imaging, it is deemed important to provide a basic overview of the phenomenon of interest and its basic structure, as this is often referenced in later sections. Wakes are generated by the movement of the hull of a ship through the sea surface. While the generation of wakes is a complex phenomenon which is affected by the sea state, ship characteristics, and the speed of the vessel, several common features can be generally identified in remote sensing imagery of high enough resolution. These features are highlighted in Figure 1.

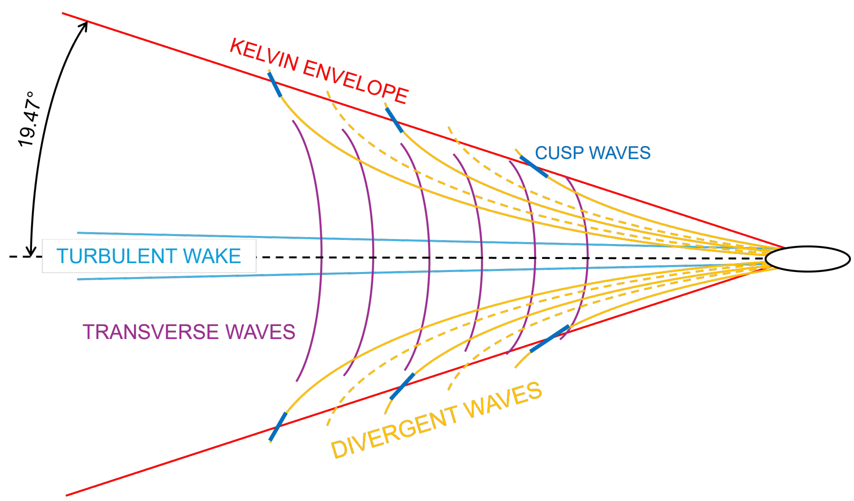


Figure 1. Schematic synthesis of the basic structure of a ship wake with the hypothesis of infinite depth. Divergent waves are divided into crests (continuous lines) and troughs (dotted lines).

In general, the wake field of a ship is generated by the interaction of a stationary wave pattern and a turbulent wake. The stationary wave pattern travels at the same velocity as the ship and is formed by divergent and transverse waves. These are usually well-defined for displacement ships, which are, in general, slower. The propagation of these wave groups is bounded within the so-called Kelvin angle, which, under infinite depth conditions, is always equal to 19.47° [13]. In real conditions, this angle varies, becoming narrower with increasing speeds when above a threshold depending on the characteristics of the vessel. A turbulent wake, instead, is generated by the boundary layer effects of the hull of the ship. For ships mounted with propellers, the most common propulsion system in use, the turbulence is further increased. Pichel et al., in the "Ship and Wake detection" chapter of their "Synthetic Aperture Radar Marine User's Manual" [2], divide wake structures into four categories:

- Turbulent wakes, which stretch directly behind the vessel. With favorable conditions, a turbulent wake can be observed for several kilometers behind the ship itself.
- Kelvin wakes, formed by transverse and divergent waves. Divergent waves, as they propagate outwards from the track of the vessel, interact with transverse waves and generate a V-shaped pattern of cusp waves. These wave groups are strongly influenced by the depth of the seabed and the Froude number of the vessel, as shown in Equation (1):

$$\mathrm{Fr} = \frac{u}{\sqrt{gL}}, \tag{1}$$

  where u is the local flow velocity (in m/s), g is the local gravity field (in m/s^2), and L is a characteristic length (in m) usually selected as the ship's length along the center-line [14].
- Narrow-V wakes, visible through Bragg scattering from short centimeter-scale waves along the vessel.
- Internal wave wakes, generated under certain conditions of shallow stratification.

Generally, the bow of the ship creates a system of waves whose wavelength is related to the ship speed but not necessarily to the ship length [14].

Before analyzing capabilities for detection of ship wakes using SAR, it is important to note that the detection and analysis of wakes in SAR images is further complicated by the fact that the wake image that is observed using SAR does not correspond to an instantaneous snapshot of the wake itself. The SAR collects data over a period of time, leading to phenomena such as hydrodynamic modulation and velocity bunching. Consequently, the wake characteristics that can be observed depend significantly on the relative geometry between the wake and the direction of motion of the SAR-mounting platform [15]. The other parameter that has a great effect on wake visualization in SAR imagery is wind speed, due to its influence over sea surface roughness [2].

In SAR imagery, turbulent wake is the most visible of the ship-related signatures after the ship itself. This type of wake appears as a dark line (due to its smooth surface) stretching from the ship and up to a few kilometers behind it. Although less common than turbulent wake, Kelvin wakes are imaged in higher-resolution SAR imagery. It is often the case that only one Kelvin arm is visible, or even only its cusp waves. This is often due to the relative geometry between the SAR and the wake, as previously stated. A narrow-V can sometimes be seen in SAR imagery, usually at low wind speeds (less than 3 m/s). Finally, internal wave wakes are only observed in regions of shallow water stratification, under moderate wind conditions (3 to 10 m/s).

The internal waves generated by a moving ship mostly occur in coastal waters where water stratification is strong because of the mixing of freshwater and seawater [16]. They are more apparent in L-band imagery than they are in X-band or C-band imagery, and they are significantly more distinct if the SAR sensor is perpendicular to the ship track.

Another characteristic of wakes in SAR images is the azimuth offset of the wake and the hull [3,5]. This effect is proportional to the Doppler shift effect of the back-scattered signal in SAR, and, thus, can be re-conducted to the slant range component of the speed of the ship. Some studies have exploited this effect to obtain an approximate evaluation of ship velocity, proving an interesting capability.

Tings et al. studied the detectability of wake components using different SAR sensors through quantitative and qualitative analyses [17], as well as the non-linear dependencies of oceanographic characteristics and the said detectability [18]. They found that near-hull turbulence and turbulent wakes are not significantly influenced by C-Band or X-Band frequencies or by slant range variations. However, Kelvin wakes are more detectable at shorter slant ranges, due to the scattering effects of tilt modulation, hydrodynamic modulation, and velocity bunching. This effect diminishes with increasing slant ranges, making Kelvin wakes less detectable. Narrow-V wakes, primarily caused by Bragg scattering, are better detected by X-Band sensors than C-Band sensors, as X-Band's shorter Bragg wavelengths align more effectively with the wakes. The study also confirmed that ship wakes are generally more detectable in TerraSAR-X imagery compared to RADARSAT-2 and Sentinel-1, likely due to the prevalence of Bragg-based wake components.

In optical imagery, wake appears very differently. Because of an easier interpretability, there are less studies on the ways ship wakes appear in optical images. In 2018, Liu and Deng [16] provided basic information for ship detection and identification by observing and summarizing the features of different types of ships and their wakes in optical images. Their focus was mainly on turbulent wakes and Kelvin wakes in Gaofen GF-1 satellite images. The turbulent region appears as a bright trail in optical images, since bubbles significantly increase the reflectivity, almost equally in each band. This is especially true for the smooth regions of turbulent wakes, and for parts of Kelvin wakes.

Liu et al. [19], while proposing a hull detection method with cascaded wake detection, conducted a statistical analysis of a large amount of ships with varying Froude numbers. They found that fishing vessels with short hulls often only generate turbulent wakes visible in satellite imagery, while motorboats (with very short hulls) also produce two visible bright narrow V-shape Kelvin arms. Bigger vessels, like cargo ships and warships, can produce visible Kelvin wakes, and, depending on their speed, they may also generate striped wakes and internal waves.

Kelvin waves are of particular interest, as they contain a plethora of valuable information on ships. For example, the propagation of a transverse wave, if one is generated, can be related to the speed of the ship that generated it (the propagation velocity of the wave's center is the same as the speed of the ship). Furthermore, the reflectance of Kelvin waves is deeply influenced by the draft of the ship, as well as its speed, width, and length [13]. While it is widely recognized that Kelvin waves appear in remote sensing images with meter-level resolution, valuable information contained within these images is sometimes overlooked. For instance, the speed of a ship generating a transverse wave matches the propagation velocity of the wave's center.

Regarding the optical sensing of ship wakes, there is a fervent interest in the use of infrared bands. This is because there is a difference, both in surface roughness and temperature, between the wake structures generated by the passage of a ship and the background. In this context, researchers speak of a "thermal" wake, formed by the cooling water and exhaust heat discharged by a ship, framed by a cold wake formed by the cool water in the lower part of sea that rises to the surface due to the ship propeller and the rolling vortexes generated by the hull [20]. Zhang et al. [21] characterized the infrared response of a ship wake through simulations using a ray tracing method with different detecting conditions; Yang et al. [20] developed and tested different simulating models of infrared imaging of ship wakes based on different sources of radiance and their transmission through the atmosphere.

One general output from all of these studies is that there is a strong dependence of the wake radiance on the observing geometry (i.e., the observer zenith angle). Van Iersel and Devecchi [22] modeled the infrared and radar signatures of wakes, in particular the characteristic V-shaped Kelvin wakes, comparing them in different wind and vessel speed conditions. They concluded that the Kelvin wake is more visible at low wind speeds with a flat sea surface, and that higher vessel speeds are needed the higher the sea state becomes. They also noted that, in general, radar observations allow for a better signal than infrared for higher sea states.

Another characteristic of wakes that can be exploited for detection comes from the application of the Fourier transform. When analyzing the frequency spectrum, Kelvin wake and turbulent wake have stable X-shaped and linear distribution patterns, respectively [19,23]. An example of this pattern is shown in Figure 2. While this pattern is predictable given the geometrical nature of the structures under discussion, analysis in the frequency domain can be useful to isolate the aforementioned components of wakes from sea clutter. In particular, the shapes of these patterns do not significantly change due to varying sea states or illumination conditions, contrary to sea clutter, which exhibits a more distributed pattern in the frequency domain [10].

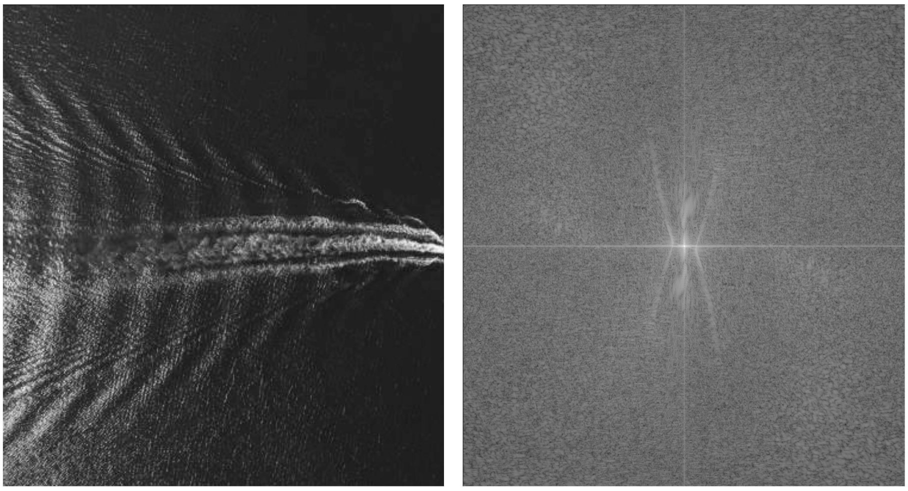

(a) (b)

Figure 2. (**a**) Gray-scale optical image of a ship wake. (**b**) Fourier transform of the same image

As is true for all spaceborne remote sensing, and more specifically for object detection, spatial resolution is a critical parameter. In this sense, ship wake detection has a clear advantage when compared to simple hull detection: the wake of moving vessels is, in general, a larger target. In fact, as previously discussed, some of the structures of a wake can extend for kilometers behind the generating ship. This characteristic is especially interesting when dealing with the detection of small ships.

In optical imagery, spatial resolution has been shown to be significantly more important than spectral resolution [11], with wake detection methods performing better in high-resolution panchromatic imagery than multi-spectral imagery, with the previously discussed exception of thermal infrared bands. This has been shown to be true for SAR imagery as well [24].

When referring to maritime surveillance, there is also something to be said for revisit time requirements. D'Errico et al. [25] analyzed the re-observation capabilities of complex satellite systems involving different radar constellations. Their study found that re-observations occur rapidly, at fractions of the orbital period, but there is an average "blind" interval of about 12 h due to the inherent limitations of the commonly selected sun-synchronous orbits. While utilizing multiple-satellite systems greatly increases the frequency of successive observations compared to a single satellite or constellation, it still does not ensure continuous observation throughout the day, unless sparse constellations are also employed. This is an inherent limitation that should be considered when developing a spaceborne monitoring system.

3.2. Overview of Traditional Methods of Wake Detection

Traditional methods of wake detection exploit the common features of ship wakes to discriminate them from other phenomena present in image acquisitions of the sea surface. The main characteristic feature of wakes that has been traditionally used in this context is their linear wedge-like shape. Therefore, the traditional approach to wake detection includes several methods and transforms able to detect straight lines in images. Other methods have been developed and tested over the decades. The following subsections serve to highlight these different methodologies for both SAR and optical imagery.

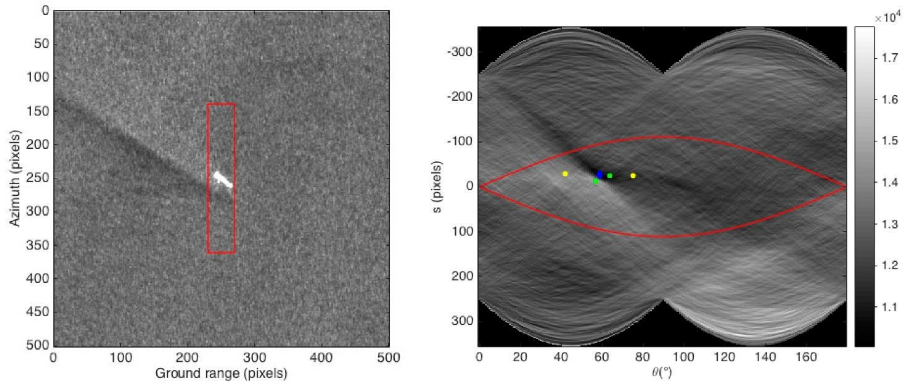
3.2.1. Methods Based on the Extraction of Linear Features

As stated, the most common traditional approaches for ship wake detection are based on exploiting their linear structure. The most common methods used in this context to detect straight lines [6] in images are RT [26], the Hough transform [27,28], and the scan curve [29]. These methods are applied to images, turning a line detection problem into a simpler task closer to the detection of dark or bright spots.

Of the three, the RT is the most commonly used for wake detection [3,30–38]. The RT is an invertible transform that was first published by Johann Radon in 1986 [26]. A form of the RT for a 2D image f(x,y) is given by Equation (2):

$$\begin{gathered}\iint_{x,y} f(x,y)\delta(x\cos\theta + y\sin\theta)\,dx\,dy,\\ -\infty < x < \infty,\\ -\infty < y < \infty,\\ 0 \le \theta < \pi.\end{gathered} \tag{2}$$

where (x $\cos\theta$ + y $\sin\theta$) is the range ρ in the Radon-transformed space. The RT was not originally intended for line detection, but it fits the task for images of the sea. This is because ship wakes are either very bright or very dark, while the sea returns are generally average. When all the pixels of a given line are bright, and the others are closer to dim, in the Radon-transformed space the particular ρ and θ of the line are highlighted [7]. A threshold can then be used to extract these peaks and isolate straight wake structures. Figure 3 shows an example of RT usage for ship wake detection.



(**a**) (**b**)

Figure 3. (**a**) Original Sentinel-1 image, where the red rectangle indicates a mask used to cover the ship and propeller wake returns; (**b**) detected wake features in the Radon domain. Two red sinusoidal curves define the restricted Radon domain. The blue diamond is the turbulent wake, the green squares are the narrow-V wakes, and the yellow dots are the Kelvin arms. Reprinted with permission from Ref. [39]. 2017, Graziano et al.

It is necessary to note that, while ship wakes are characterized by linear features, they do not appear as ideal lines with uniform brightness in satellite imagery, due to noise, clutter, and other atmospheric or sea surface phenomena. Thus, ship wake detection using traditional methods may lead to poor accuracy. Enhancing the linear features of wakes from space [3,29,31–43] is insufficient to reduce false detections due to other linear phenomena, for example, those that might be generated by waves.

Some applications used other forms of processing to further enhance the wakes in imagery before or after using RT or other line-based transforms [8]:

- Wavelet transform was used to sharpen wake edges using the frequency difference between sea clutter and wake stripes [37]. Krishnaveni et al. [44] proposed a wake detection method for SAR imagery using wavelet filters together with the RT.
- Recent studies have used the idea of compressed sensing to separate wake signals from sea clutter. A so-called low-rank plus sparse decomposition (LRSD) algorithm was used to suppress sea clutter and extract wake components [32,38].
- Sparse regularization was used to enhance linear features of the RT [31,45].

The scanning-based method was first described in [29]. It starts by computing the mean picture brightness in all directions surrounding the object ship to create a scanning curve. From this curve, one can infer the likely wake direction. By using pre-processing to improve the wake signal, Nan et al. [46] and Björn and Domenico [47] increased algorithm performance. A Kelvin arm's alternating light and dark streaks were found by Wei et al. [48] using a periodic function as the scanning curve. Recognizing that Kelvin wakes exhibit distinct periodic patterns due to the interference of divergent and transverse waves forming at specific angles relative to the ship's heading, they modeled the Kelvin arms as sinusoidal periodic surfaces through nonlinear fitting of the wave elevation data. By applying Floquet theory, the T-matrix method, and the extended boundary condition method (EBCM), they derived the scattering cross-section formula for a finite periodic dielectric surface representing the Kelvin arms. Their simulations analyzed how ship speed, shape parameters, and incident angles influenced the scattering intensity distribution of the wakes.

Most of the studies referenced above only focused on a relatively small manually selected subset or localized data from their respective imagery. Moreover, transforms are often applied locally, sometimes after hull detection [12]. Indeed, the issue of false alarms and failed detections due to surface marine phenomena significantly reduces the range of successful applicability of these traditional methods of detection. In this sense, the DL-based methods analyzed in the following section have a powerful advantage, in that they are able to learn hidden and complex patterns at various scales in the data, as long as enough properly annotated data are provided for their training.

Regardless of the issues with these methods, knowledge of them is an important starting point. Tools such as RT are powerful in their simplicity and can be integrated into DL-based wake detection processing chains to improve their performance [10].

3.2.2. Methods Based on Polarimetric Enhancement

One interesting recent development came from Yanni Jiang et al. [49], who explored the application of SAR imagery for detecting ship wakes in the ocean, particularly under challenging conditions such as high sea states. Polarimetric SAR (PolSAR), which captures the polarimetric properties of target backscatter, was tested as a potential solution to enhance ship wake features.

The authors proposed a methodology that included the simulation of fully polarized SAR imagery of ship wakes (both turbulent and Kelvin types) using a two-scale composite model. A polarimetric whitening filter (PWF) and polarimetric detection optimization filter (PDOF) were applied for feature enhancement, and a pre-processing approach involving logarithmic transformation and z-score normalization was used to mitigate the impact of bright and singular points. They also employed a RT-based method for detecting ship wakes in various polarimetric conditions, demonstrating an average improvement of nearly 50 percent in wake detection performance using PWF and PDOF compared to traditional HH and VV polarizations.

Their findings suggest that polarimetric enhancement methods, particularly PWF and PDOF, can significantly improve the detection of ship wakes in SAR imagery by reducing the influence of sea clutter and enhancing the visibility of wake features. However, a dark turbulent wake becomes almost invisible after PWF and PDOF, and sometimes single artifact points are created which may cause misdetections. Their study showed that wakes were generally correctly detected in VV polarization, and only partially in the other polarizations.

3.2.3. Other Methods

Several other methods of wake detection have been developed throughout the years, mostly focusing on SAR products, due to their inherent advantages for maritime surveillance, but exploiting different methodologies and domains.

Fast computation and rapid detection were the focus of Liu et al. [50], Chen et al. [51], and Yang et al. [52]. Liu et al. proposed a frequency-domain-based method that leverages the fast Fourier transform (FFT), achieving fast computation and low complexity for real-time ocean surveillance and practical SAR systems. Their approach capitalizes on the "V" pattern waves generated by moving ships, which are detectable by SAR. Chen et al. [51] utilized a dynamic threshold and morphological filtering to binarize and clean the detection region, followed by a linear fitting method to confirm long ship wakes, with the final aim of a rapid detection method to identify long ship wakes in SAR images. The method leverages SAR imaging parameters and the ship's axial direction to pinpoint potential wake detection areas. The authors then tested their method on ENVISAT and GF-3 SAR data. Finally, Yang et al. [52] proposed a method for SAR imagery using sparse regularization and a Cauchy prior. This method enhances linear features in the RT domain by employing the Cauchy proximal operator and the Moreau–Yoshida unadjusted Langevin algorithm (MYULA) for computational efficiency and robustness. They experimented with their method on imagery from COSMO-SkyMed.

Sea state conditions and their impact on detection were analyzed in [53,54]. An anomaly-detection-based method to enhance ship wake detection in SAR images across various sea states was the topic of Guan et al. [53]. Traditional methods using RT and other methods based on detection of linear features operate best in conditions of calm seas, as the presence of excessive surface roughness and other sources of surface clutter can result in a significant increase in false detections. The method by Guan et al. leverages image reconstruction errors from dictionaries trained on sea clutter images to identify anomalies. Ship wake detection was framed as an anomaly detection problem, where the reconstruction errors of ship wakes exceeded a certain threshold set by anomaly detectors. They utilized three anomaly detectors—isolation forest (iForest), local outlier factor (LOF), and one-class support vector machine (OCSVM)—to distinguish ship wakes from sea clutter. The issue of complex background conditions was also addressed by Yang et al. [54], who proposed morphological component analysis (MCA) and dictionary learning to decompose the SAR image into a "cartoon" component with ship wakes and a sea-background texture component. The method adaptively learns separate dictionaries for these components and then uses a shearlet transform to enhance the ship wakes in the cartoon component. The enhanced wakes are detected using the principal component (PC) transform.

Multi-image or multi-object detection has, finally, been the topic of other works, starting from Liang Zhang [55], who explored the application of ship wake detection in SAR images for the Chinese Coast Guard's monitoring and enforcement capabilities. Their study reviewed several algorithms for ship wake detection, including two-parameter CFAR, K-distribution-based CFAR, multi-polarization detection, and multi-image correlation methods. Ding et al. [56] proposed a method to detect multi-ship and multi-scale wakes in SAR products. Their method detects highlighted pixel areas and generates specific windows around centroids to identify wakes of varying sizes. It uses wake clustering to locate all wake components and statistical features to determine the visible length of wakes. Testing on Gaofen-3 SAR images demonstrated the effectiveness of the method. The approach involves a specific window search that reduces the detection area, utilizing a localized Radon-based enhancement algorithm to screen real ship targets and accurately locate wake axes. Then, Liu et al. [19] proposed a method for cascaded detection of ship hulls and wakes using high-resolution satellite optical imagery from Gaofen-1. Candidate hulls are identified using the phase spectrum of the Fourier transform, followed by hull refinement to acquire accurate shapes and eliminate false alarms based on shape and texture features. The inclusion of wake information is used to increase the probability of correctly identifying true ships. Detected ships are classified using a fuzzy classifier that combines hull and wake information.

Wang et al. [24] investigated the detection of Kelvin ship wakes in numerically simulated SAR images using advanced signal processing techniques. They modeled the Kelvin wake geometry based on classical ship wave theory and calculated the scattering echo using a two-scale method. To detect the wakes within these images, they reconstructed them in the Radon domain using Cauchy proximal splitting (CPS), incorporating a non-convex regularization. They found that Kelvin wakes are more readily detectable in HH polarization, at larger incidence angles, and in the X-band frequency range.

3.3. Introduction to DL-Based Methods for Wake Detection

While applications based on the RT are extremely common, it is known that they are limited to small images, often centered around the vessel, and work best with low-wind conditions. Other traditional applications of wake detection from airborne and spaceborne remote sensing imagery, while based on different processes, generally have issues with different working conditions (i.e., hull characteristics, hull speed, wind conditions, illumination conditions, etc.) and with the presence of too much sea clutter. DL-based applications have shown the ability to overcome these limitations. It is not a surprise, then, that research on wake detection has moved onto DL-based solutions, empowered by the ever-increasing availability of high-quality spaceborne remote sensing data.

Object detection is the task of detecting single or multiple instances of certain objects of a certain class (such as cars or buildings) in digital images and videos. Object detection in spaceborne remote sensing imagery has its own specific set of challenges, related to very high background-to-foreground ratios, and more specific characteristics related to the respective sensing platforms [57]. When focusing on ship wake detection, as previously explained, one should remember that ship wakes appear differently in optical and SAR images. In both cases, successful detection depends on both spatial and spectral capabilities.

One important thing to note about DL-based applications is that they require large datasets for training, validation, and testing purposes [58]. Not only do the data need to be numerous, but they need to be of high quality (relative to the application of interest) and correctly labeled. In the recent decade, the need for high-quality data has resulted in the generation of several benchmark datasets. Common examples of these are COCO (Common Objects in Context) [59] and ImageNet [60]. In a field that progresses as rapidly as AI, these benchmark datasets provide stable ground for comparison between models, which is precious to researchers and developers alike. Moreover, pre-trained weights for these benchmark datasets are available for most common state-of-the-art architectures, and can represent a great starting point for more specific applications through the application of transfer learning.

Although simple datasets of ship wakes have been collected for both SAR [8,61,62] and multispectral spaceborne images [10,13,63,64], currently there is no benchmark dataset for wake detection. Information on the few high-quality freely available ship wake datasets is compiled in Table 1, including information on their imagery and corresponding links.

One notable case from the abovementioned table is the SynthWakeSAR dataset [66] by Rizaev and Achim, which was developed in terms of ship classification based on synthetic SAR images of wakes. While this work is not further explored in this review, as it is not strictly related to wake detection, it is a notable reference regarding the possibility of extracting vessel information directly from the appearance of their wake, without the need of AIS data.

Table 1. A short list of open high-quality ship wake datasets.

Reference	Dataset	Image Type	Images Characteristics	Annotations	Links (Last Accessed 27 September 2024)
[10]	Ship Wake Imagery Mass (SWIM)	Optical	768 × 768 pixels Google Earth optical images (2.5-m to 0.5-m resolution). 11,600 positive examples and 3010 negative examples, up to 15,356 wake instances	Oriented bounding box and landmarks	https://www.kaggle.com/datasets/lilitopia/swimship-wake-imagery-mass
[65]	OpenSARWake	SAR	This collection provides 3973 1024 × 1024 pixels SAR images of two polarization modes. 4096 instances. Bands L, C, X, with resolutions going from 1.25 m to 12.5 m	Oriented bounding box	https://github.com/libzzluo/OpenSARWake
[66]	SynthWakeSAR	Synthetic SAR	10 ship models for a total of 46,080 images. 0.96 × 0.96 km scene, 3.3-m azimuth and range resolutions. 227 × 227 × 1 pixels. Noised and despeckled images provided.	Classification annotations	https://data.bris.ac.uk/data/dataset/30kvuvmatwzij2mz1573zqumfx

While these datasets exist, new publications on novel wake detection methods are almost always accompanied by their own proprietary datasets with specifically structured annotations. In this sense, it is hard to separate a DL-based wake detection application from its accompanying dataset. Therefore, the following subsections will also contain information on the datasets gathered by the respective authors and the types of annotations they feature.

It is important to note that dealing with datasets of satellite imagery poses more limitations than natural images like those from the COCO and ImageNet datasets. For example, when applying data augmentation to SAR imagery, it is important to keep in mind that some standard operations like simple rotations and flips may not have physical significance and could thus introduce errors into the learning process if applied without careful consideration.

In conclusion, it is deemed necessary for the usability of this review to provide a quick introduction to several concepts that are useful to better understand DL architectures and, more specifically, DL-based object detectors. The following subsections contain such an overview.

3.3.1. Backbone, Neck, and Heads

When analyzing detection models, and DL architectures in general, three different parts can usually be identified: these are commonly known as the "backbone", "neck", and "head" [67]. Figure 4 summarizes the basic idea behind this division into a more digestible scheme.

The backbone is the part of the detection architecture that extracts features from the input imagery. This denomination is often used interchangeably with the word "encoder", since the extraction of feature maps can be considered analogous to a representation problem. Backbones are usually characterized by a CNN, where the input imagery goes through a series of convolution operations and non-linear activation functions to extract significant features and patterns in the data. After each convolution, the data can be downsampled through pooling operations, allowing subsequent convolutional layers to extract higher-level features with higher semantic values but lower spatial resolution. One thing to note is that CNNs are not the only solution to feature extraction, as Transformer-based backbones are also gaining traction [68].

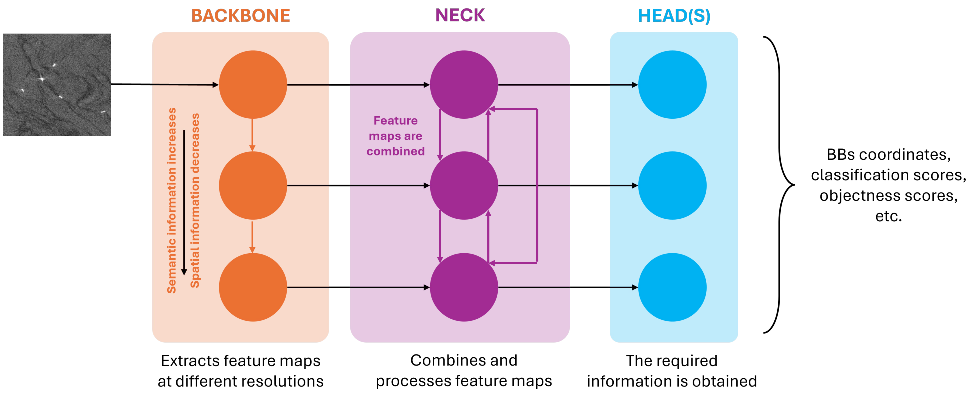


Figure 4. A schematic view of a detection model, divided into backbone, neck, and heads. The backbone module extracts the essential features at different resolutions and at different levels of spatial and semantic values. The neck combines the feature maps in various ways. Finally, multiple head modules produce the finals outputs, from the localization of objects, their classes, or any other information the model is designed to provide.

The neck takes the feature maps generated at various levels by the backbone as input and combines them in various ways. The combination of maps from different levels serves to enrich feature maps with higher semantic value with the spatial context of higher-resolution maps. The basic idea is that, after all the downsampling applied to obtain these high-level feature maps, the information regarding the position of objects would be partially or completely lost without some form of recombination. A classic neck architecture was introduced with feature pyramid networks (FPNs) [69].

Finally, the heads of the network are tasked with outputting the desired results by feeding combinations of the processed data to specifically designed layers, often fully connected layers (also called "dense" layers). The simplest detection models will usually output the coordinates of regressed bounding boxes (BBs), with the predicted class of the detected objects accompanied by some form of confidence score. For semantic segmentation tasks, the outputs will consist of masks related to every class.

It is important to note that the previous overview is very general, and that significant differences and exceptions can be found in the literature and in working applications. In the last decade, the field of DL-based CV has significantly evolved, with innovations being presented every day and large investments both in the private and public sectors. Throughout this evolution process, different paradigms have emerged, like single-stage and two-stage detectors, as well as anchor-based and anchor-free architectures. The following subsections serve to highlight some of these differences, accompanied by state-of-the-art examples.

3.3.2. Single-Stage and Two-Stage Detectors

DL-based object detectors are usually categorized into two-stage and single-stage detectors [57]. The following subsections describe the main differences between the two types of detectors and provide examples regarding the evolution and state-of-the-art of such models.

The first detection models developed were the two-stage detectors, a categorization which refers to the sequential application of two processes:

- Region proposal is performed by region proposal networks (RPNs), where the image is scanned for a set number of regions in the image that most likely contain objects of interest. In general, the output on an RPN will be a set number of BB proposals and scores representing the probability of the presence of objects at each location.
- Classification, where the content in each BB is classified as one of the object classes of interest or discarded as background. During this stage, BBs are also adjusted through regression to better fit the detected objects.

The first DL-based detection algorithms were very slow and inefficient, as they used intuitive but computationally inefficient methods of region proposal, such as sliding windows. Nowadays, region proposal has become much more efficient, and two-stage detectors are still used at large scale. Common examples of two-stage detectors include the R-CNN family of networks (e.g., R-CNN, Fast R-CNN) [70,71].

Differently from two-stage detectors, single-stage or one-stage detectors use pre-generated candidate regions as region proposals, applying object classification and BB regression directly. When compared to two-stage detectors, this approach sacrifices a certain amount of accuracy in exchange for smaller networks with less parameters and increased processing speed. Representative examples of one-stage detectors are the single shot multibox detector (SSD) [72] and its descendants, and the family of you only look once (YOLO) models [73–77]. By approaching the detection task as a single-shot regression, YOLO implements a grid-based approach to predict class probabilities, BBs, and the relative confidence scores.

It is important to note that research in the field of maritime surveillance favors single-stage detectors, which provide better characteristics for real-time or near-real-time applications, due to being lighter and, in general, more efficient. A 2023 survey conducted by Li et al. [78] on real-time ship detection in SAR imagery showed a clear prevalence of one-stage detectors for this type of application, with architectures based on several versions of YOLO being widely favored in 37 out of the 70 reviewed works. This is consistent with similar works related to DL-based ship detection in optical imagery [79]. However, as shown in the following sections, for wake detection, both one-stage and two-stage detectors are found, with a prevalence of custom architectures developed specifically to tackle this challenge.

3.3.3. Anchors and Key-Points

Detection models can also be divided into anchor-based and anchor-free categories [57,80]. Anchors are predefined BBs of various scales and aspect ratios that serve as references for predicting the presence and location of objects within an image [81]. These anchors are densely tiled across the image, ensuring comprehensive coverage and the ability to detect objects at different scales and orientations. The primary advantage of using anchors is their capacity to standardize the prediction process, allowing models to learn to predict offsets from these anchor boxes to the actual object boundaries, thereby facilitating the detection of a wide range of object sizes and shapes with a unified framework. It is important to note that the use of anchors requires deep contextual knowledge of the objects of interest by the developer.

In response to the complexities and limitations associated with anchor-based methods, anchor-free models have emerged as a simpler yet effective alternative. These models eliminate the need for predefined anchors, instead relying on other mechanisms to identify and localize objects.

Another possible solution is the use of key-points [57]. Models like CornerNet [82] and CenterNet [83] represent a shift towards using key-points such as object corners or centers to define the spatial extent of objects. In particular, CornerNet detects objects by predicting paired key-points for the corners of BBs, while CenterNet identifies the central point of objects and estimates their size directly. These types of solutions can also effectively make use of heat-maps, which are, in general, a natural output of CNNs.

3.3.4. Attention Modules

One of the biggest issues when it comes to accurately detecting ship wakes is the presence of a complex background. Moreover, there is the general issue in object detection that is the unbalance between foreground and background. In object detection tasks, this problems can be mitigated by the use of attention mechanisms [84].

Attention mechanisms, in general, work by re-weighting a feature map to highlight useful features and suppress background information that is semantically redundant.

Xue et al. [10] cited several works that exploit interesting attention mechanisms for their object-detection purposes:

- Pang et al. [85] increased classification accuracy by better utilizing small object contextual semantics through the usage of a global attention module.
- A spatial and scale attention module was developed by Zhang et al. [86] to allow varying kinds of objects with varying scale attributes to have varying intensity responses at each layer of the FPN.
- Yang et al. [87] used a supervised semantic segmentation method to change the weights of the features of objects of different classes into different channels and, respectively, enhanced and weakened the object and background features in the spatial domain.

In the context of ship wake detection, implementing an attention mechanism can significantly enhance a model's precision. By focusing on the wake's characteristics and minimizing the influence of the surrounding water and noise, the model can achieve higher accuracy and reliability.

3.4. DL-Based Applications for Optical Imagery

Applications for optical satellite imagery are common in the field of ship and wake detection, due to an easier interpretability than their radar-based counterparts, as well as due to the ability to use the spectral information from multiple frequencies in the near and far infrared. On this point, while in the literature there is no complete review on the topic of wake detection using DL-based methods, it is important to mention a useful review by Li et al. [12], which compiles some interesting information related to hull and wake detection methods based on infrared remote sensing.

The first interesting example of wake detection in optical satellite imagery came from Xue et al. [10]. Their focus was on developing an end-to-end detector named WakeNet, based on CNNs. One innovative idea to come from WakeNet is the addition of a specific head (see Section 3.1) for regression of the wake tip coordinate and Kelvin arm direction. Moreover, they applied a spectral and a multi-scale attention module (MSAM) which exploits the X-shaped wake spectral pattern. In particular, WakeNet is a single-stage anchor-based object detection network composed of four modules:

1. A backbone CNN for feature extraction.
2. An FPN with a MSAM that enhances the contextual spatial relevance of feature maps at different scales.
3. Classic heads for oriented bounding box (OBB) classification and regression
4. An additional head for landmark regression.

Using the property of frequency domain wake images, the backbone for WakeNet integrates a ResNet with a frequency channel attention module. In this way, the network extracts the wake texture features in the image domain, while also learning the wake features in the frequency domain.

Apart from the usual classification and BB regression heads, another head is added for landmark regression. In particular, since Kelvin arms are often the most prominent feature of ship wakes in optical imagery, WakeNet regresses the wake tip and the direction of the Kelvin arms. These landmarks also serve to indicate the heading of the ship, which could not be automatically extracted from just the OBBs. Because of this multi-task concept, WakeNet minimizes the multi-task loss function shown in Equation (3) during its training phase:

$$L(p,t,q) = L_{\text{class}}(p,p^*) + \lambda_1 L_{\text{OBB}}(t,t^*) + \lambda_2 L_{\text{landmarks}}(q,q^*), \tag{3}$$

where L_{class}, L_{OBB}, and $L_{\text{landmarks}}$ represent the classification loss, OBB regression loss, and landmark regression loss, respectively. The idea is that the landmarks are mainly used for auxiliary supervision, and thus are weighted less. The landmark head the authors developed also included the use of the RT, to improve the regression of the angles of the line features of the Kelvin arms, as the transformed feature map, and thus the peak detection task was deemed to be more compatible with the nature of a convolutional layers with a rectangular receptive field.

To develop WakeNet, Xue et al. [10] gathered their own dataset of about 11,600 optical images, which they called SWIM (Ship Wake Imagery Mass), that is available for researchers. One particular feature of the dataset are its annotations, including both BBs and landmark labels, as well as providing a discrimination for instances with “difficult” labels. The dataset contains 14,610 visible waveband satellite and aerial images and can provide up to 15,356 annotated wake instances, with images of spatial resolution from 2.5 m to 0.5 m.

Another interesting application came from Esposito et al. [63]. They proposed an application of a Mask R-CNN [88] for instance segmentation of ship wakes in Sentinel-2 imagery. The authors focused on imagery from Sentinel-2, considering B2 (blue), B3 (green), B4 (red), and B8 (near infrared) bands, which are all at 10 m. These images were gathered into a dataset , which was called the Ship Wake Dataset (SWD), containing 766 examples including single and multiple wakes, as well as negative examples with no wakes, all validated using AIS data.

Liu and Zhao [13] approached the problem of low data availability using simulated data to enhance their dataset, focusing on Kelvin wake detection in optical imagery. In particular, they employed a point source perturbation, simulating a specific motorboat in a fixed velocity range, coupled with sea surface slope probability density functions. With this approach, they paid particular attention to the specular reflections of sunlight on the wake regions, which are crucial for Kelvin wake identification in optical imagery, and to accurately simulating the reflectance for each pixel. They populated their dataset, including examples of different illumination and observation geometries, by simulating different Sun zenith angles and satellite zenith angles.

These synthetic examples enhanced a dataset composed of 2124 wake samples from Gaofen-1 2 m resolution panchromatic imagery and 8 m resolution multi-spectral imagery. The authors then adopted the GoogLeNet architecture, built on Inception modules [89], which substitutes dense layers with sparse ones, thus significantly reducing the computational efficiency. Their general framework employs pre-processing of the input image, followed by clipping it into overlapping sub-images, which are then classified as either Kelvin wakes or natural surfaces. The clips containing wakes are then merged to highlight the areas covered by wakes. This framework successfully turns a detection task into a much simpler classification task, with an process much akin to classic two-stage detectors using region proposals.

The authors also tested their methods by removing wake regions distant from ship hulls, which were manually logged, and labeling ships that did not produce Kelvin wakes as true negatives. The results presented an increase in precision and a slight decrease in recall, as many false positives occurred in areas far away from any identified ships. One final output of interest comes from their study of multi-spectral imagery and the possibility of enhancing the resolution of color and infrared bands using pan-sharpening. However, they noted that the original panchromatic images yielded the most efficient detection outcomes, indicating that high-resolution spatial details are the most critical for identifying Kelvin wakes.

In 2023, Del Prete et al. [64] developed and validated a novel DL approach for detecting ship wake components in electro-optical satellite imagery based on the detection of the key-points of wake components. By employing a transfer-learning procedure to fine-tune ImageNet weights, the authors were able to train a lightweight model based on the EfficientNet architecture [90] with a smaller custom dataset made of Sentinel-2 multi-spectral images and corresponding AIS data.

Their method demonstrated robustness across different spectral bands and a heading accuracy under 10°. Del Prete et al. [64] demonstrated the model’s effectiveness on lower-resolution Landsat-9 images, confirming its generalizability. The authors also noted that their approach should be applicable to SAR data, advising the use of ensemble or cascade methods to address false positives, and noted that denoising techniques should be thoroughly investigated.

A very recent contribution came from Liu and Zhao [11], who tackled the challenge of Kelvin wake detection in large-scale, high-resolution optical imagery. Recognizing the scarcity and limited diversity of real Kelvin wake samples, they proposed a method that utilized simulated Kelvin wakes to augment their training dataset. These simulations were generated based on physical models of wake formation and imaging mechanisms, focusing on accurately reproducing the specular reflections of sunlight on the wake regions, which are crucial for Kelvin wake identification in optical imagery.

Their approach involved dividing large-scale GF-1 optical images into overlapping sub-images of 224 by 224 pixels. They employed a deep neural network, specifically GoogLeNet with inception modules [89], to classify each sub-image as containing a Kelvin wake or a natural sea surface. By merging the classified sub-images, they effectively detected and delineated wake regions. This framework transformed the detection task into a simpler classification problem, similar to classic two-stage detectors using region proposals.

Liu and Zhao's method achieved a high recall rate of 94.0% and demonstrated that high-resolution spatial details are critical for detecting Kelvin wakes. Interestingly, they found that incorporating multispectral data through pan-sharpening did not improve the detection performance, indicating that the original high-resolution panchromatic images were most effective. They also experimented with removing wake regions distant from ship hulls—manually logged to simulate known ship locations—which increased precision and slightly decreased recall. This suggested that many false positives occurred in areas far from any identified ships.

3.5. DL-Based Applications for SAR Imagery

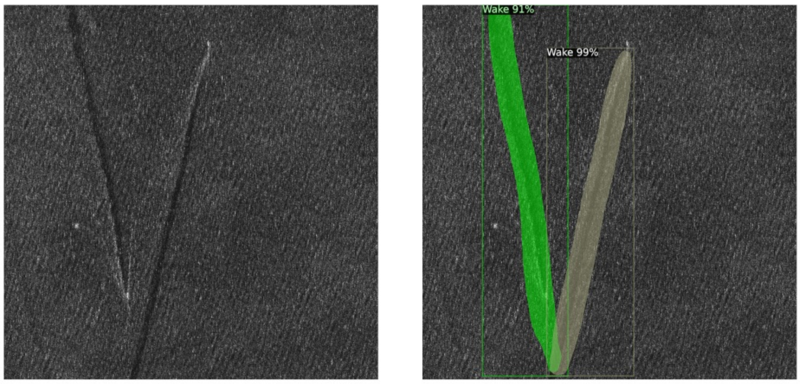
SAR-based maritime monitoring has been the subject of fervent study by the scientific community due to its all-weather all-time characteristics. In fact, research on wake detection methods using SAR imagery is much more common than with optical imagery, making use of its characteristics and looking for smart ways to approach the problem that often do not involve DL. However, traditional methods of wake detection in SAR imagery are often based on threshold evaluations and are naturally susceptible to high false alarm rates, not only due to the presence of clutter, but also due the inevitable presence of speckle. In this sense, learning-based methods can help to improve performance, by being more robust against any kind of interfering factor.

The first publication analyzed in the context of SAR-based applications came from Del Prete et al. [61]. This work, published in 2021, represented the first DL approach to specifically detect ship wakes without any a priori knowledge, and without more specific information about the location of the vessel that generated the wake. The authors first introduced the field as a whole, with a complete analysis of the field of DL-based detectors, then deployed several architectures on the same custom SAR wake detection dataset to evaluate the strengths and weaknesses of each.

The dataset in question, called SSWD (SAR Ship Wake Dataset) by the authors, includes 261 wake chips extracted from Interferometric Wide (IW) swath Sentinel-1 SAR images with VV polarization and with a pixel resolution of about 10 m $\times$ 10 m (ground range $\times$ azimuth), with particular attention paid to obtaining a reasonable statistical distribution of orientations of instances. Polygon annotations were used to overcome the problem of the narrow shape during the random rotations in the data augmentation strategy.

The authors selected several object detection architectures, testing 21 combinations of different backbones and necks, including Faster R-CNN [91], Mask R-CNN [88], Cascade Mask R-CNN [92], and RetinaNet [93]. All combinations were tested, starting from transfer learning of pre-trained weights on the ImageNet and COCO benchmark datasets.

The best performing model from their evaluation was Cascade Mask R-CNN with a ResNet + FPN backbone, which showed a robust performance in wake detection, despite the challenges posed by coherent speckle-noise. The authors, noting the performance of the Cascade approach, further explored its generalizability by testing its performance on X-band SAR images from TerraSAR-X and COSMO-SkyMed satellites, evaluating its detection capabilities across different sensors, resolutions, and polarization. The model demonstrated strong generalizability when applied to X-band SAR images, indicating its potential versatility across different radar imaging platforms and conditions. An example of the application of the model to X-band SAR is shown in Figure 5.



(**a**) (**b**)

Figure 5. Subset of a TerraSAR-X product in VV polarization (azimuth–slant range coordinates). (**a**) Reference image. (**b**) Segmentation results of the model based on Cascade Mask-RCNN. Adapted with permission from Ref. [61]. 2021, Del Prete et al.

As previously stated, the interest in security and surveillance applications regarding ship and wake detection has pushed a significant subset of the field towards lightweight solutions that can offer near-real-time capabilities, as timeliness is highly valued in this context. Thus, Ding et al. [8] focused on developing a lightweight DL-based ship and wake detector trained on Gaofen-3 imagery, which was primarily intended for embedded devices in a military context. In particular, they used a YOLO-like structure with some specific modifications and an attention mechanism.

In line with the "lightweight idea", their backbone has only three layers, which are also not traditional convolution-batch normalization-activation layers, but combined convolution layers (CBC) specifically developed by the authors for this application. These modules involve the use of squeeze and excitation (SE) modules [94], enabling them to perform dynamic channel-wise feature re-calibration.

It is important to note that the SAR images in the application in question are used as gray-scale images, as polarization and multi-channel image information are deemed less critical. Similarly to in previously described applications, the linear features of the wake are exploited to enhance the capabilities of the model. In particular, horizontal BBs are used in conjunction with the wake line (considered as the turbulent wake), which is aligned with the diagonal of the corresponding BB. To do this, intersection over union (IoU) is insufficient, and an angle-IoU loss function is proposed to achieve high angular correlation. This angle-IoU is defined as the normalized angular distance coefficient between actual and predicted wakes, as shown in Equation (4):

$$RAIoU = \frac{|\theta^p - \theta^g|}{\theta^c}, \tag{4}$$

where the superscripts p, g, and c denote the prediction box, the ground truth, and the smallest enclosing box covering two boxes, respectively. This angular consideration was further improved by adding a distance loss between the diagonal of the predicted BBs and the actual wake line. Finally, Ding et al. [8] developed a loss function which takes into consideration integrity, coincidence degree, and directionality, which they identified as the critical elements for a wake BB.

As with previous applications, Ding et al. also collected a dataset for their training and testing activities. Their dataset contained 862 pairs of ships and wake SAR images from Gaofen-3, containing different scales of ship and wake images in various sea conditions and imaging modes, including spotlight, stripmap, and scan, to ensure diversity.

Wang et al. [62] used YOLOv5 for their application, which focused on detecting non-linear ship wakes and weak wakes in SAR images. The authors made large use of simulated data to augment their dataset of SEASAT SAR and TerraSAR-X imagery, using a semi-deterministic facet scattering model (SDFSM) to simulate the electromagnetic scattering distribution of the sea surface and Kelvin ship wakes. The modeling process involved generating a composite scene of the sea surface and ship wake, simulating various conditions such as different sea states, ship speeds, and headings. Then, key parameters like the radar incident frequency, radar incident angle, ship dimensions, and sea surface wind speed were used to generate realistic SAR image simulations. The authors then employed several models to simulated various facets of the scene:

- The sea surface was simulated utilizing the Elfouhaily wave spectrum and Mitsuyasu directional function to simulate the sea surface's randomness and anisotropic characteristics.
- A Kelvin wake mathematical model was used to simulate the wake's wave height, considering ship speed and direction.
- An SAR image simulation was obtained combining the facet scattering distribution and the SAR imaging mechanism to produce SAR images of the composite sea surface and wake scenes under various conditions.

The authors compared the performance of YOLOv5 with traditional RT-based methods. According to their analysis, the DL-based solution successfully detected the non-linear wakes, while methods based on linear feature extraction were obviously unable to succeed.

Finally, in early 2024, Xu and Wang [65] addressed the scarcity of publicly available SAR ship wake datasets by introducing OpenSARWake, a large-scale dataset annotated with oriented bounding boxes, as cited in Table 1. To effectively detect ship wakes, they also developed SAR Wake Net (SWNet), a two-stage detection algorithm tailored for SAR imagery. Recognizing that the attention mechanisms commonly used in optical image processing may not enhance performance in SAR tasks, due to complex sea clutter and often indistinct wake features, SWNet utilizes a ConvNeXt-T [95] backbone and introduces a specifically developed feature pyramid network called HR-FPN*. Their method achieved a mean average precision (mAP) of 49.0%, outperforming existing approaches on the OpenSARWake dataset. Their work served to highlight the importance of designing specialized network architectures that consider the unique characteristics of SAR images in ship wake detection.

3.6. Final Overview

A complete overview of all previously referenced methods, together with their advantages, disadvantages, and image sources is provided in Table 2. Further meta-level analysis is provided in the Discussion Section.

Table 2. Summary of referenced ship wake detection methods.

Reference	Type	Method	Advantages	Disadvantages	Imagery Source
[31]	Traditional, SAR	Radon Transform (RT) with filtering (e.g., Wiener filter)	Effective for detecting linear features; increases SNR; filters reduce false alarms	High false alarm rate without post-processing; requires additional filters	Seasat-A (L-band)

Table 2. *Cont.*

Reference	Type	Method	Advantages	Disadvantages	Imagery Source
[32]	Traditional, SAR/Synthetic	Localized RT using Feature Space Line Detector (FSLD) algorithm.	Robust against noise; better localization of short and curved wakes	Computationally intensive; less accurate for long wakes without full coverage	Seasat-A and simulated imagery
[29]	Traditional, SAR	Digital terrain models for masking land; RT for wake detection	Fast system; reduces false alarms; demonstrated on ERS-1 and Seasat data	Higher false wake detection in ERS-1; some ships missed (7.4% Seasat, 8% ERS-1)	Seasat-A, ERS-1
[33]	Traditional, SAR	RT with band-pass filtering and non-linear amplification	Enhances detection of faint wakes; effective preprocessing steps	Dependent on wake appearance and image quality; may not eliminate all false positives	N/A
[37]	Traditional, SAR	Localized RT combined with wavelet filter (LRTWF)	Detects linear and chirp-like features simultaneously; robust to Gaussian noise	Increased computational complexity; local	N/A
[50]	Traditional, SAR	Frequency-domain linear feature detection (FLD).	Reduces computational complexity by 20–40%; feasible for real-time detection.	Requires pre-processing to reduce false alarms; careful threshold adjustment needed	Real and synthetic SAR data
[35]	Traditional, SAR	Fast Discrete Radon Transform (FDRT); speed estimation from wake spectrum.	Efficient speed and beam estimation; works with Kelvin and turbulent wakes.	Limited to straight ship paths; less accurate for maneuvering ships	Airborne SAR (X-band)
[38]	Traditional, SAR	RT with stochastic matched filtering.	Reduces speckle noise; enhances wake features.	Higher computational cost due to interpolation at each rotation angle.	SIR-C/X-SAR, ERS SAR
[44]	Traditional, SAR/Synthetic	RT combined with wavelet filters for denoising	Improves SNR; enhances wake detection in noisy images	Higher computational complexity; struggles with heavy noise	N/A
[42]	Traditional, SAR	CFAR detection using signal-to-clutter ratio (SCR) enhancement and Normalized Hough Transform (NHT).	Enhances wake detection in terms of SCR; improves performance of CFAR	Usual weaknesses of thresholding and line detection	RADARSAT-1, TerraSAR-X
[46]	Traditional, SAR	CFAR detection based on length normalized scan	Higher accuracy than Radon/Hough transforms; accurate velocity estimation	Requires ship detection beforehand; computationally complex	COSMO-SkyMed, ERS-2, RADARSAT-1/2
[4]	Traditional, SAR	Classic RT application for heading extraction	Simple to apply	Inherits weaknesses of RT	COSMO-SkyMed and TerraSAR-X
[21]	Traditional, Optical (IR)/Synthetic	Infrared imaging model using Cook–Torrance model and ray tracing	Comprehensive environmental modeling	Difficult to model all environmental conditions accurately	Synthetic data

Table 2. *Cont.*

Reference	Type	Method	Advantages	Disadvantages	Imagery Source
[54]	Traditional, SAR	Morphological dictionary learning with component analysis	Outperforms traditional methods; effective in complex backgrounds	Computationally complex; requires quality initial dictionaries	ERS-2
[3]	Traditional, SAR	Wake feature identification using hydrodynamic theory; azimuth shift for heading and velocity	Better than simple thresholding; simple application	Low agreement among methods	COSMO-SkyMed and TerraSAR-X Stripmap
[36]	Traditional, SAR	RT-based detection of turbulent and narrow-V wakes; azimuth shift for estimation.	Accurate detection; robust against noise and multiple wakes.	Tested on limited images; ineffective for curvilinear wakes.	TerraSAR-X, COSMO-SkyMed
[39]	Traditional, SAR	RT with classification and feature validation on Sentinel-1.	High detection accuracy (78.5%); robust against false confirmations.	Some false confirmations (18.5% on Kelvin arms).	Sentinel-1
[34]	Traditional, SAR	Dual-stage Low-Rank Plus Sparse Decomposition (LRSD) with RT.	Robust wake detection; effective under heavy clutter.	Computationally intensive due to dual-stage processing.	COSMO-SkyMed
[40]	Traditional, PolSAR	Polarimetric LRSD and RT for clutter reduction	High precision; effective clutter reduction and classification.	Not tested in adverse weather conditions	UAVSAR airborne SAR
[51]	Traditional, SAR	Detection using Doppler shift curve analysis and linear fitting	Fast detection; effective for long wakes	Less effective for short wakes; requires precise parameter tuning	ENVISAT ASAR, GF-3 SAR
[48]	Traditional, Synthetic SAR	Periodic structure scattering using Floquet theorem and EBCM.	Useful for synthetic applications; efficient scattering calculation	Limited to Kelvin wakes; excludes turbulent wakes	Synthetic data
[52]	Traditional, SAR	Wake detection using Cauchy regularization	Enhanced performance with Moreau Yoshida unadjusted Langevin algorithm (MYULA)	Computationally complex; requires fine-tuning	COSMO-SkyMed
[30]	Traditional, SAR	RT for wake detection with two-step validation	Effective for detecting go-fast boats; reduces false alarms	Requires favorable sea and wind conditions	TerraSAR-X Stripmap
[45]	Traditional, SAR/Synthetic	Inverse problem approach with sparse regularization and RT	Handles wakes as inverse problem	Lower performance on low-resolution images; computationally demanding	TerraSAR-X, COSMO-SkyMed, Sentinel-1, Advanced Land Observing Satellite 2 (ALOS-2), Synthetic
[6]	Traditional, Optical	RT of images with centered hulls; verification of true wakes	The demonstrated principle is interesting for post-processing	Requires hull-centered imagery; inherits RT weaknesses	Gaofen-1, Sentinel-2, Landsat-8

Table 2. *Cont.*

Reference	Type	Method	Advantages	Disadvantages	Imagery Source
[55]	Traditional, SAR	Detection using two-parameter CFAR and multi-image correlation	Suitable for wide-area monitoring; high accuracy	Difficulties in complex sea backgrounds; sensitive to sea conditions	N/A
[43]	Traditional, SAR	RT-based detection for identifying dark vessels	Effective in homogeneous sea clutter; reconstructs wake lines	Struggles with sharp wind transitions or surface films	Sentinel-1
[56]	Traditional, SAR	Multi-ship and multi-scale wake detection using RT enhancement	High accuracy; effective on complex wakes; no large datasets needed	May miss small wakes; challenging in complex backgrounds	Gaofen-3
[53]	Traditional, SAR	Anomaly detection using sea clutter dictionaries	Improves detection under varying sea states; adaptable to complex environments	Requires extensive training data; computationally intensive dictionary learning	HRSID dataset
[19]	Traditional, Optical	Cascaded hull and wake detection using Fourier transform; fuzzy classifier	Cascaded approach is effective; of great interest	Higher computational requirements	Gaofen-1 panchromatic and multi-spectral
[24]	Traditional, Synthetic SAR	Non-convex regularization with Cauchy-based penalty	High accuracy in simulated conditions; sensitive to ship parameters	Limited to simulated data; unverified in real conditions	Numerically simulated data
[49]	Traditional, Synthetic SAR	Pre-processing with polarimetric enhancement	Enhanced detection using PWF and PDOF filters	Complex pre-processing; mitigation of bright points needed	Synthetic data
[5]	DL, SAR	Vessel velocity estimation via azimuth offset using CNNs; RT for wake highlighting	Validated with AIS data; effective velocity estimation	Inherits RT weaknesses; issues with dark ships in AIS data	TanDEM-X Single Look Complex (SLC) images
[10]	DL, Optical	CNN architecture exploiting X-shaped wake patterns and RT	Combines CNN with traditional knowledge; effective detection.	Inherits weaknesses of traditional CNNs	Google Earth imagery (0.5–2.5 m resolution)
[61]	DL, SAR	Wake detection using Cascade Mask R-CNN	Robust detection in Sentinel-1 images; generalizes to X-band data.	High false alarm rate in rough seas; limited dataset size	Sentinel-1, TerraSAR-X, COSMO-SkyMed
[63]	DL, Optical (Multi-spectral)	Wake detection using Mask R-CNN	High accuracy in complex scenarios; effective in multiple configurations	Requires large training dataset; sensitive to weather conditions	Sentinel-2
[62]	DL, SAR	Nonlinear wake detection using electromagnetic scattering model and YOLOv5	High efficiency and accuracy; detects weak wakes in complex seas	Requires high computational power; some limitations in high sea states.	SEASAT, TerraSAR-X, Synthetic SAR data

Table 2. *Cont.*

Reference	Type	Method	Advantages	Disadvantages	Imagery Source
[64]	DL, Optical	Keypoints method using deep learning for wake recognition	High accuracy; fast processing; lightweight model for edge devices	Struggles under poor conditions; limited to optical images	Sentinel-2, Landsat-9
[8]	DL, SAR	Lighter version of YOLOv4 for efficiency; detects ships and wakes	Novel method; more efficient than classic YOLOv4	Small dataset used in study; may limit generalizability.	Gaofen-3
[11]	DL, Optical/Synthetic	Kelvin wake detection from large-scale optical imagery using simulated data trained deep neural network	High accuracy (Recall 94%, Precision 70.8%), effective use of simulated data to address data scarcity	Moderate precision, requires synthetic data to compensate for limited real wake samples	Gaofen-1
[65]	DL, SAR	Presented OpenSARWake dataset. Tested several architectures on it. Feature Refinement Oriented Detector (SWNet)	Large-scale SAR dataset, multi-band data, diverse wake types	Moderate mAP, challenges with complex sea clutter and small targets in SAR images	Sentinel-1A, TerraSAR-X, ALOS-PALSAR

4. Discussion

The main problems that every ship wake detection method has to face are as follows:

- Several sources of clutter are present on the marine surface, which can cause a higher rate of false positives. Furthermore, these sources of clutter vary greatly in their appearance [24,96] and can be difficult to filter out;
- The quality of wake imaging is strongly dependent on local and, often, global meteo-marine conditions. Even with SAR, which is heavily researched due to its all-weather all-time capabilities, the visualization of wake structures is influenced by wind, sea, and local atmospheric conditions;
- The mechanism behind wake generation is not consistent at a high-level analysis, and real images often feature different combinations of wake structures, if any at all;
- Wake detection near coasts and low depth areas is, in general, particularly problematic and requires different considerations. Very few works have focused on wake detection in these conditions;
- Ship wake detection is limited to moving ships.

Table 3 contains an overview of the methods cited in this review. As previously stated, applications on SAR imagery have been investigated more thoroughly than optical imagery. While traditional methods have been investigated for at least three decades, DL-based techniques are newer and growing in number. Publications referenced in this review regarding ship wake visualization or detection in airborne or spaceborne remote sensing images were not included in the table if they did not propose and test a solution to tackle the task.

Figure 6 contains a timeline of referenced publications involving wake detection methods up to April 2024. The trend shows an increased interest in the topic in the last decade, and the recent increase in DL-based solutions. Nonetheless, traditional methods still prove of great interest to the scientific community.

Table 3. Overview of referenced publications proposing and testing solutions for wake detection.

	Traditional	Deep Learning
SAR	29	5
Optical	3	4
TOTAL	41	

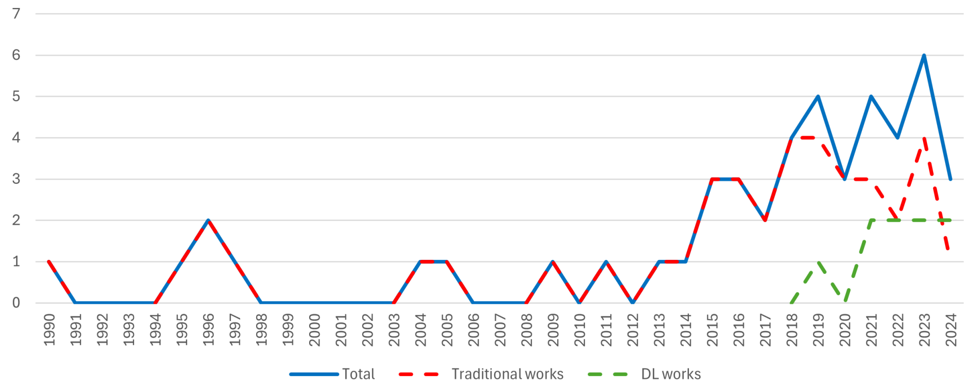


Figure 6. Year-by-year timeline of referenced publications on traditional and DL-based wake detection. Updated up to April 2024.

Of the traditional methods, those based on RT and other linear feature extraction methods are the most common. However, these encounter issues when facing non-linear wakes, strong sea clutter, and any conditions that do not allow the formation or conservation of linear features in the remotely sensed scene. Nonetheless, these methods are still powerful and are often paired with other techniques and transforms, which can enhance their performance.

Recently, DL-based methods have proven their capabilities in terms of overcoming some of the aforementioned weaknesses. Comparative studies have shown that DL-based methods outperform traditional techniques, particularly in complex and high sea state conditions. For example, Wang et al. [62] demonstrated that YOLOv5 could detect non-linear and weak wakes more effectively than RT-based methods. Similarly, the lightweight DL model proposed by Ding et al. [8] achieved real-time detection capabilities suitable for embedded systems, highlighting potential for practical, real-world applications.

However, the lack of a well-recognized large benchmark dataset for ship wake detection hurts the field, as data availability is the most important factor for the development, training, and validation of learning-based methods. At the time of writing, each new work on the topic requires a significant expenditure of time and resources to develop a well-annotated dataset that suits its focus.

Nonetheless, there is a clear growth of interest in the field, as maritime surveillance remains a topic of great strategical importance. The use of synthetic data is an interesting solution to the issue of low data availability, and represents a feasible and powerful approach that cab be paired with the usual techniques of data augmentation.

Moreover, there is unexplored potential for the use of more advanced architectures and methodologies, such as vision-transformer-based detectors and physics-informed DL, which may incorporate hydrodynamic laws or information related to local meteo-marine conditions. As a final remark, hitherto, the multi-spectral (in electro-optical imagery) or the multi-polarization (in SAR data) content of wake images and features has remained largely unexplored or underutilized for both wake detection and false alarm reduction.

5. Conclusions

Ship wake detection is a powerful tool that can be used to effectively enhance existing hull detection methods. In fact, it has been proven that precious information such as heading, speed, and even hull shape and dimensions can be reliably extracted from the appearance of ship wakes in spaceborne remote sensing imagery. Both optical and SAR applications were explored in this work, highlighting their differences, as well as their strengths and weaknesses.

The field has evolved significantly in the past decades, transitioning from traditional linear feature extraction methods to advanced DL-based approaches. While effective in detecting basic linear features, traditional methods based on RT and Hough transforms are limited by high false alarm rates and sensitivity to sea clutter. Applications based on other concepts have also been developed and presented in this overview, proving how much exploration has been carried out on the topic.

Recently, DL-based applications have demonstrated superior performance in detecting complex wake patterns under varying environmental conditions. The integration of attention mechanisms and multi-task learning has further enhanced detection accuracy. The generation of synthetic data has proven crucial in overcoming the scarcity of annotated datasets, enabling DL models to generalize well to real-world conditions. Lightweight DL models, designed for embedded systems, offer promising solutions for real-time maritime surveillance and security applications.

To advance the field of ship wake detection, several key areas require further research and development. The creation of standardized benchmark datasets for wake detection would facilitate the comparison of different models and foster collaboration among researchers. Developing more sophisticated data augmentation techniques that fit the characteristics of the respective types of satellite imagery, including better simulations of diverse maritime conditions, could enhance the training of DL models. Improving the interpretability of DL models and their robustness to adversarial conditions is essential for reliable real-world applications. Furthermore, combining wake detection models with other maritime surveillance systems, such as information from the AIS, could provide a more comprehensive solution for monitoring and tracking vessels. Finally, the inclusion of information regarding sea characterization and the sources of sea clutter could offer interesting solutions to reduce false positives.

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