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Far-Field Wake Modeling for Automatic Ship Detection from Satellite Imagery

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Abstract. The problem of the so-called dark vessels is a major security issue related to the marine traffic and environment. In this respect, the automatic ship detection from satellite imagery is one of the possible countermeasures in the fight against illegal activities. Technically, such a way of detecting dark vessels mainly relies on the identification of the far field wake released by a hull which might be visible over a significant distance from the hull itself and which might last in the water surface for a reasonable amount of time to be seen by a satellite. However, the shape and the persistence of such a wake field, which includes both the steady wave pattern and the turbulent wake behind the hull, is strongly affected by other phenomena mainly related to the weather conditions, then including the presence of surface wind waves or other patterns on the sea surface. Moreover, there might be unfavorable conditions for the satellite to produce accurate images to be used in this recognition process. This complex situation is faced in a project funded by the Italian Ministry of University and Research called UEIKAP (Unveil and Explore the In-depth Knowledge of earth observation data for maritime Applications) in which an Artificial Intelligence (AI) system for the automatic identification of dark vessels from optical and SAR (Synthetic Aperture Radar) images is under development. The training of the AI framework is based on both publicly available image datasets and ad-hoc synthetic data. The latter are generated by using Computational Fluid Dynamics simulations on a set of hulls in different operating conditions. The proposed analysis focused on the numerical issues related to the prediction of the far-field wake of a hull in the light of the final purpose of the UEIKAP project. A comparison of two different CFD approaches is shown and discussed in terms of pro and cons of both methods and the obtained results.

Keywords. Ship far-field wake, Waves, Computational Fluid Dynamics (CFD), Synthetic Radar Aperture (SAR)

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1. Introduction: overview of the dark vessels detection problem

The ability of recognizing uncooperative vessels without transponders (dark vessels) plays a key role in both the civil and military fields, but having the whole picture of a vessel situation is not an easy task. Despite regulations Despite onboard Automatic Identification System (AIS) transponder are mandatory for large vessels such as cargo ships greater than 500 gross tonnage, ships engaged on international voyages, and passenger ships of any size (1), most vessels are not required to transmit such a type of data. Any of those latter ships can be seen as a so-called *dark vessel*. So the only way to monitor their activity is by using non-cooperative systems. In this context, ships moving at the sea free surface are themselves a source of relevant information, ranging from actual and past position, heading, speed, even the vessel size and in some cases the hull type (2). Trough the UEIKAP project (Unveil and Explore the In-depth Knowledge of earth observation data for maritime Applications) (3; 4), founded by the Italian Ministry of University and Research, a deep learning-based framework for wake detection by optical and synthetic aperture radar (SAR) space borne remote imagery is under development. In particular, a dataset of real and simulated imagery is building to be used as train set for a landmark-based detection model able to exploit the characteristic features of ship wave patterns. This, coupled to an in-depth sea characterization and a meteo-marine conditions study, will be able to properly discriminate sea surface clutter for the objects of interest, reducing or justifying possible false or missed detections.

2. Numerical methods for the far-field wave prediction of a ship

Predicting the far field wave pattern of a ship is a complex task for several reasons including for instance the wave dissipation models, the effect of complex bathymetries or the computational burden required as the size of the numerical domain increases. Typical numerical methods used in the naval architecture field are developed to focus on the accurate ship performance prediction. This means that usual domains have dimensions in the order of few ship lengths. Dealing with SAR images, the sea area that is covered is the order of kilometers. This is a change of perspective that needs to be handled in a computational framework.

The far field wave pattern of a moving ship has been predicted by using a depth-averaged horizontal two dimensional (2DH) model which resolves the time dependent short wave action on the scale of wave groups, while infra-gravity wave motions and mean flow are computed using the nonlinear shallow water equations, implemented trough the XBeach software (5). XBeach has been originally developed to analyze coastal processes such as sand dune erosion by water (6) and it has been used in several applications involving, among the other, storm processes (7), wave transformation in the nearshore (8), vegetation effects on wave propagation in shallow water (9). As a term of comparison, classic CFD computation of wave patterns developed by using openFOAM solver have been shown to highlight the differences with resect to the proposed approach. This RANS (Reynold Averaged Navier Stokes) approach has been widely applied in different ship related problems from resistance prediction, maneuvering performance assessment to complex hydrodynamics at bow (10; 11; 12; 13; 14). It is based on a different numerical scheme which is well treated in literature (15) and it is typically used to achieve accurate local flow solutions which include the effect of viscosity.

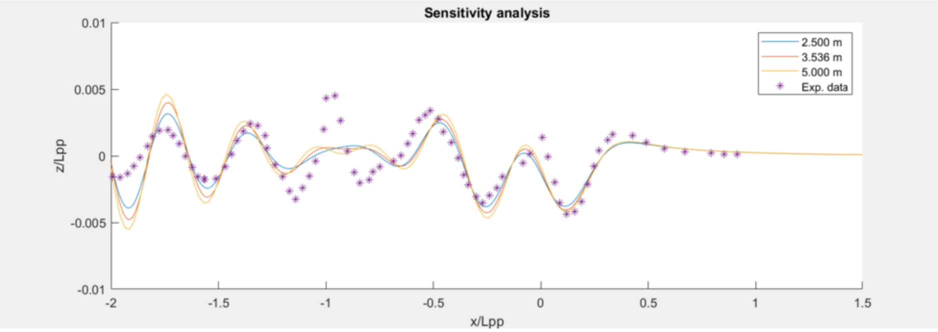

Figure 1. Comparison of the measured and predicted longitudinal wave cut of the KCS hull at $y/L_{BP} = 0.15$.

3. Results: validation, comparison of the proposed CFD approaches and systematic analysis

The selected CFD approaches have been compared in the light of the main object of the project. As previously recalled, the final goal is to train a deep learning neural network to recognize the passage of a dark vessel from SAR images. Then, the focus of the CFD analysis won't be, as usual, on the prediction of the resistance but it aims at the qualitatively prediction of a consistent wave pattern which will be used in higher level training process.

Two cases have been tested. The first is a conventional displacement hull represented by the KCS (KRISO Container Ship), a well known benchmark case which has been widely used in several computational and experimental studies (16; 17; 10). The second selected hull is derived by the NPL series. It is a classic hull which is typically used for fast displacement ships of small to medium size (18; 19).

The KCS hull has been first analyzed to compare the XBeach prediction of the longitudinal wave cut of the generated steady wave pattern with measurements from towing tank experiments. As shown in Figure 1, representing the longitudinal wave cut at $y/L_{BP} = 0.15$, the main wave train, within the range $-0.5 < x/L_{BP} < 0.5$, is captured by the numerical prediction with a reasonable accuracy. The far field wake field is well predicted too but the first wave hump right behind the hull. This portion of the wave profile, approximately in the range $-1.2 < x/L_{BP} < -0.8$, is mainly driven by strongly non linear effects related to the flow field at the stern of the hull. Such effect cannot be reproduced by using the pressure disturbance scheme adopted by the XBeach model. In addition, a sensitivity analysis on the cell size of the computational domain has been carried out. These results are shown in the same Figure 1, highlighting that there is a relatively small effect on te height of the peaks of the wave in the far field while their position is not affected by this parameter.

The wave patterns of the NPL hull at different speeds have been computed by using XBeach solver in several conditions. Five ship speeds have been considered, ranging from 5 to 25 knots for variation of the depth of the bottom from a minimum of $d/L = 0.18$ to a maximum of $d/L = 2.5$, depending on the size of the boat. No inlet/outlet boundary conditions have been used for the flow, so the ship moves within the domain. This first set of tests have been carried out considering a straight pattern, where the ship is able to reach the stationary condition (constant speed) in about 200 meters. The domain used in

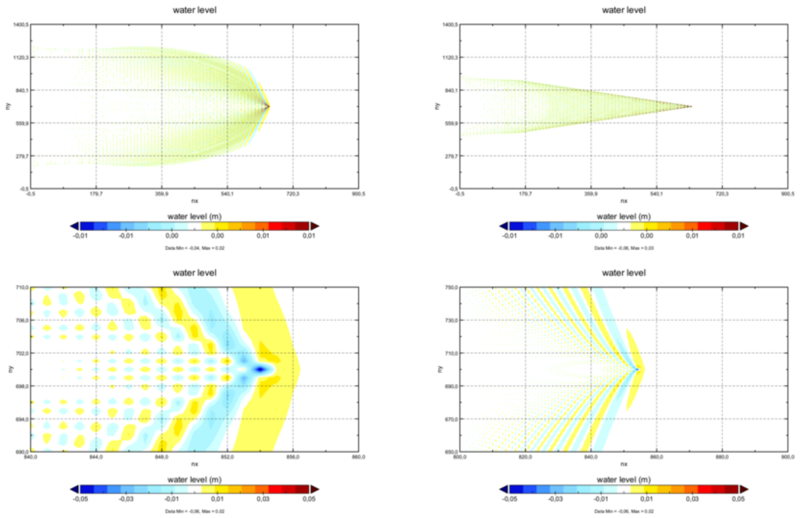

Figure 2. XBeach prediction of the wave pattern of the NPL hull with $L = 5m$, $V_S = 5\ knots$, at $d/L = 0.5$ (upper, left), $d/L = 2.5$ (upper right). Lower row: two zooms close to the hull at $d/L = 0.5$.

the analysis is very large, compared for example to classic computations for resistance prediction, in the order of about 7 km x 4 km. The size of the computational domain has been kept for all the test, then resulting in different overall cpu time of each analysis. On average, once the other settings of the simulations have been selected according to a preliminary sensitivity on the wave patter prediction, each run of the solver takes, on average, 5 hours. Figure 2 displays some results computed on the smaller hull. In particular, the same ship speed at two increasing depth ratios are shown in the upper row, highlighting the capability of the XBeach solver to capture the effect of the depth of the bottom. Indeed, at the lowest depth ratio the wave pattern is mainly made of transverse waves with an angle even higher than the Kelvin one, which is instead kept at the highest depth ratio, corresponding to an infinite depth condition. In the lower row of plots, two close ups of the wave pattern of the first case with the lower depth ratio are shown. The waves in the hull near field, recalling that the hull is not represented by a physical surface, are predicted in terms of global trends but, as expected, with a precision that cannot be considered acceptable for in depth analysis of the local flow. As a term of comparison, the wave patterns of the same ship, scaled to $L = 5\ m$ have been computed by using openFOAM at three different speed, corresponding to $V_S = 5, 10, 15\ knots$, at infinite depth of the bottom. It can be noted that both the positive and negative amplitudes of the waves are higher compared to those predicted by XBeach while the shape of the wave field is overall comparable. At the higher speed (bottom plot of Figure 3) bow wave breaking is occurring. This can be seen in the fragmentation of the bow wave. Such a phenomenon, which is not captured in the XBeach predictions, results in a local modification of the flow field which is not particularly relevant in the context of the far field prediction of the wave pattern.

Another set of results is shown in Figure 4 for the NPL scaled to $L = 15\ m$. Two speeds are presented, corresponding to $V_S = 10\ knots$ in the upper row and $V_S = 25\ knots$ in the lower one, both computed at two depth ratios, namely $d/L = 0.3$ in the left col-

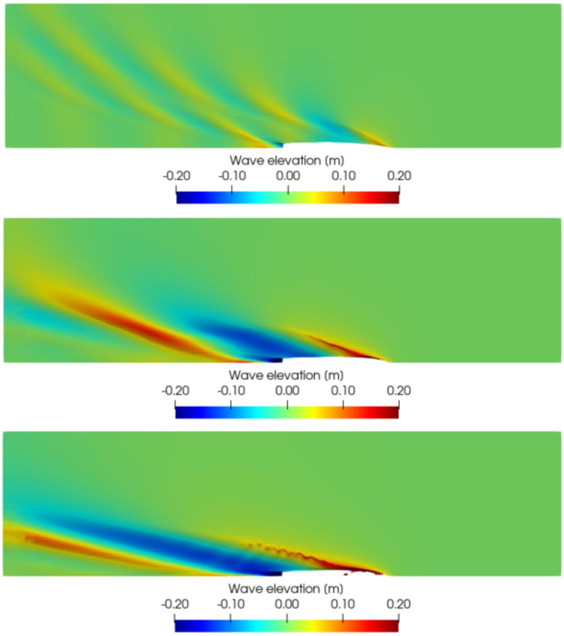

Figure 3. Predicted wave pattern of the NPL hull at three speeds $V_S = 5, 10, 15$ *knots* by using openFOAM.

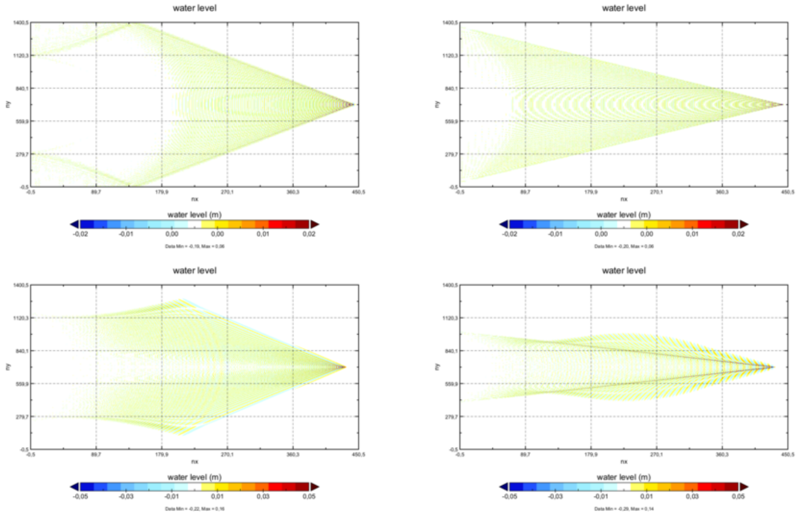

Figure 4. XBeach prediction of the wave pattern of the NPL hull with $L = 15$ m, $V_S = 10$ *knots* (upper row) and $V_S = 25$ *knots* (lower row) , at $d/L = 0.3$ (left column) and $d/L = 1.6$ (right column).

umn and $d/L = 1.6$ in the right one. Compared to the previous case with $L = 5$ m, the Froude numbers based on both the length $Fn = V_S/\sqrt{g \cdot L}$ and the depth of the bottom $Fn = V_S/\sqrt{g \cdot d}$ are smaller, resulting in more conventional shapes of the wave patterns. Particularly at the highest speed of $V_S = 25$ *knots* the acceleration phase is more evident from the far field wake which is still developing. Such a kind of simulation might be

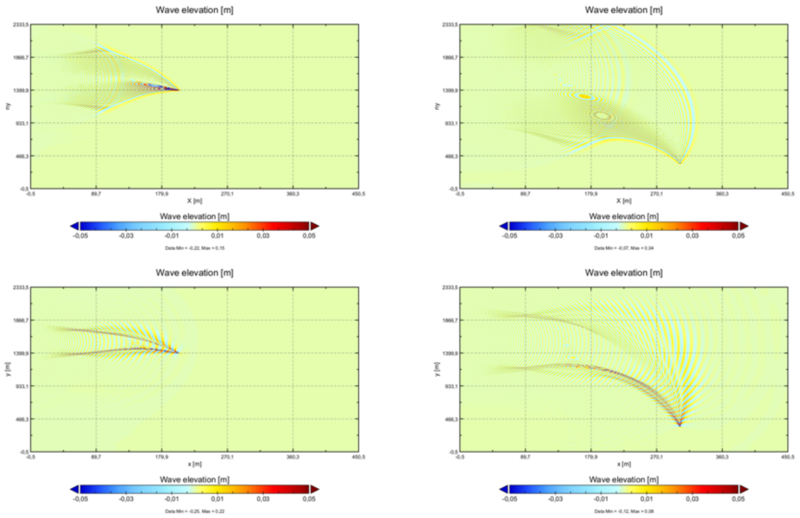

Figure 5. XBeach prediction of the wave pattern of the NPL hull scaled to $L = 20\ m$ at $V_S = 20\ knots$. Upper row: $d/L = 0.25$. Loer row: $d/L = 1.25$. Two consistent time instants have been chosen for the left and right columns.

useful too in the training process of the AI architecture to detect possible cases of ships that suddently moves from a rest position.

As an example of simulations of realistic operating conditions, a set of tests have been carried out considering a different motion pattern, resembling a turning starboard. The NPL hull scaled to $L = 20\ m$ has been chosen at $V_S = 20\ knots$. Two depth ratios are considered, namely $d/L = 0.25$ and $d/L = 1.25$, that is a shallow water and an infinite depth water cases. Once again it is worth noticing from Figure 5 how the global shape of the unsteady wave pattern changes due to the depth effect.

4. Conclusions

Dark vessels detection from SAR images plays a key role in fighting illegal activities at sea. This is not a straightforward task due to many boundary conditions related for example to the persistence of a ship wake field, to the presence of surface waves or other surface disturbance, to the reflection of the sea surface at the time of the acquisition of the SAR data and many other. Trough the UEIKAP project a AI-based framework to accomplish this task is under development which will use synthetic ship wake data as training sets for the training of the network. In this perspective, CFD computations of ship wave patterns in different operating conditions have been shown and the following conclusions are drawn. First, compared to conventional CFD studies in the field of naval architecture, due to the need of propagating the wave pattern in the far field of the ship, classic methods such as BEM or RANS are not suitable. Generally, BEMs are not designed to handle complex bathymetries in huge domains. The latter approach instead is mainly used to focus on complex hydrodynamics in the near field due to the computational effort required. Methods derived from coastal engineering field, such as XBeach, are directly developed to cope with wave propagation in the far field. Then, even if less accurate in the near field, they are very effective to generate and propagate ship wave patterns over large and complex domains. Despite this lower precision close to the hull, the global shape of the wave pattern of a ship is well reproduced over domains with sizes in the order of kilometers. Moreover, the effect of the depth of the bottom is captured too, allowing the simulation of ships passing e.g. close to coastal areas which might represent a significant scenario in the context of the project.

5. Acknowledgments

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