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Applications of smart technologies in oceanography and bathymetry

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Abstract: Oceanography and bathymetry are two interrelated fields that play an essential role in the maritime industry. Smart technologies are increasingly used in oceanography and bathymetry to collect and analyze data, improve predictive models, and increase the efficiency of operations. Autonomous underwater robots and vehicles are being used to collect data from the deep sea and to carry out underwater missions in areas inaccessible to humans. Data collected by such robots and autonomous underwater vehicles are processed using artificial intelligence and machine learning to provide accurate information about the underwater environment. This article presents the achievements of the Romanian-Norwegian team in the MARINTECH project, Romanian - Norwegian Strategic Cooperation in Maritime Higher Education for the enhancement of human capital and knowledge base in the field of marine intelligent technologies.

1. Introduction

Oceanography and bathymetry are two interlinked fields essential in the maritime industry. Oceanography focuses on the study of seawater and meteorological conditions. Bathymetry is the study of the shape and characteristics of the ocean floor, while in the maritime industry oceanography, and bathymetry are both used to improve navigational safety, environmental protection, and resource exploitation Oceanography, as an integrative science, studies the physical, chemical, geological, biological phenomena and processes that occur interdependently in the marine environment and atmospheric layers above the planetary ocean: waves, storms, precipitation, currents, the nature of the seabed, marine fauna and flora, the chemistry of marine waters, etc. [1,2]. The directions of use of bathymetry and oceanography in the maritime industry are as follows: ship routing planning to identify dangerous depths and unfavorable meteo-oceanographic conditions that would lead to a more efficient ship voyage; installation and maintenance of marine infrastructure to determine suitable areas for the installation of marine drilling installations, subsea pipelines, and telecommunication cables, to monitor marine environmental conditions around these installations and to carry out inspection and maintenance activities; marine environmental impact studies to monitor and assess the impact of anthropogenic activities on the marine environment (pollution, overfishing and exploration of underwater resources). This information can be used to take measures to protect the environment and avoid damage to the marine ecosystem; resource exploration to identify and assess marine resources such as oil and gas fields, mineral resources, or areas with fishing potential.

Intelligent technologies, including Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) are increasingly used in oceanography and bathymetry to collect and analyze data, improve prediction models, and increase the efficiency of operations.

2. Data and Methods

The first stage consists of collecting data about the marine environment. To collect data from the surface of the marine environment, beacons and specialized ships are used, and for deep-sea data, autonomous underwater vehicles and robots are used. They are equipped with smart sensors, high-resolution cameras, and data transmission equipment to a command point.

Underwater robotics is frequently used in oceanography and bathymetry for monitoring the marine environment (water composition and quality, temperature, salinity, etc.) so understanding changes in the marine environment and identifying potential problems; in mapping missions, needed to create detailed maps of the seabed. These charts can be used to identify areas of shallow water or obstructions to increase the safety of navigation in these areas; inspect oil rigs and other offshore underwater structures to detect potential technical problems and assist in their maintenance; marine life research and monitoring, including monitoring the behavior of marine animals and collecting data on the population and distribution of marine organisms; search and rescue at sea of missing ships or to assist in the rescue of persons in distress at sea [6]. Autonomous underwater robots can be programmed to perform various tasks in areas inaccessible to humans. [3, 4]. This approach can be more efficient and reduce the costs associated with the involvement of human crews on board research or work vessels.

Other intelligent data collection technologies that can be used from hydrographic vessels are current meters with integrated sensors to measure: current speed, direction, depth, and temperature in the coastal marine environment; single beam hydrographic probes (Kongsberg EA440 type); linear and angular motion sensors (IMEMS type); mobile DGNSS receiver; water sound speed profiler; multiparametric CTD probes (Valeport type); magnetometers for water depths of up to 150 m. These technologies are part of the Oceanography laboratory component of the Mircea cel Bătrân Naval Academy [7].

Images obtained by ocean observation technologies, sonar, and underwater video cameras are used in oceanography to study the characteristics and dynamics of water and to identify and monitor marine animals (whales, dolphins, sharks, etc.), which help to understand the behavior of these animals and monitoring marine populations. Also, the obtained images are used in bathymetry to both study ocean dynamics and identify areas with potential for natural resources, by determining water depth and bottom topography, to make detailed maps of the ocean floor as well as to identify features specific topography such as reefs and submarine canyons. This analysis can help [9].

Data collection has been done in real-time, which has helped to improve the understanding and management of the aquatic environment.

Figure 1. AR ROW1 autonomous underwater vehicle [14]

An example is the autonomous underwater vehicle developed by ANMB (AR ROW1) – Figure 1, which can be adapted for various civil applications, and marine research, but also for military purposes. The robot has the shape of a torpedo, can go down to a depth of 100 meters, and is only 90 centimeters long, which allows it to enter hard-to-reach spaces. The vehicle has four electric motors, powered by batteries, which ensure a speed of movement through the water of 2.5 meters per second. It comes standard with two projectors and a video camera that records images and transmits them in real-time via a cable to an image processing station, located either on a ship or on shore.

Another example of an autonomous underwater vehicle is the one developed by Norwegian partners within the Marintech project. They built a vehicle in the shape of a fish, propelled by a remote-controlled electric motor and equipped with a high-resolution camera that takes images from the aquatic environment – Figure 2.

Figure 2. Fish-type autonomous underwater vehicle [6]

The next stage was data-driven modeling. Intelligent technologies are being used to process data and develop predictive models to improve understanding of the marine environment and provide useful information for resource planning, risk analysis, weather forecasting, and other ocean phenomena. Data-driven modeling in oceanography and bathymetry is a process of building mathematical models that use observed data to understand phenomena occurring at the surface and in the deep sea [8].

The utility of this complex process lies in its applicability to various sensitive sectors of the maritime industry. The results of this process can be used to create the next step: seafloor maps, to understand and make predictions about water mass movements, and to predict the impact of climate change on the seas and oceans.

Oceanographic and bathymetry-based modeling is used to develop detailed seafloor maps that are used in the navigation of ships and submarines in areas of navigational hazard. Oceanographic and bathymetry-based modeling is also used to create mathematical models of water mass movements that can be applied to help predict climate change and understand how these changes may affect the oceans. Modeling based on oceanographic and bathymetric data can also be applied to identify and predict pollution levels in the seas and oceans, which is necessary for pollution prevention and environmental protection. Modeling based on oceanographic and bathymetric data can be used to identify tsunami risk areas to help protect communities in tsunami-affected areas.

Image analysis methods, including machine learning algorithms that can identify and classify objects in images, are used to analyze images obtained by sonar or underwater cameras. These algorithms can be trained to recognize marine animals or specific topographical features and to analyze images in real-time [10].

An example of the analysis of the data collected from the marine environment with the help of ML consisted of the study of the marine surface currents in the Romanian coastal area of the Black Sea. The in-situ observations used in the study were open-sourced and extracted from the Copernicus marine platform. The purpose of the analysis was to identify predictions (forecasts) that can reveal anomalies in the marine environment either related to climate change or to other factors that generate these anomalies.

The formation of sea currents is related to causes that can be hydrometeorological and astronomical. In the Black Sea, the current regime is specific to the regime of currents in an isolated body of water; it is determined by the wind regime (speed, direction, and time intervals), by the capture of the waters that have flowed here, by the variation of water density and the topography of the seabed, as well as by the influence of atmospheric circulation. The movement of sea currents is counter-clockwise, i.e. parallel to the shore and rarely in the opposite direction.

The Arima machine learning model (known as the Box-Jenkins method), which is used in statistics to analyze observations or predict future data in a series, was used to analyze the data. It is used when a value is recorded at regular intervals, from fractions of a second to daily, weekly, or monthly periods. The fundamental intuition behind time series forecasting is that the measure of a variable in one time period will depend on the measure of the same variable in a previous time period, 2 previous time periods, 3 ... and so on ARIMA is a time series forecasting model that incorporates autocorrelation measures to model temporal structures in time series data to predict and analyze future values. The autoregression part of the model measures the dependence of a given sample on a few past observations. These differences are measured and integrated to make the data models stationary or to minimize obvious correlation with past data (since linear independence and non-collinearity is one of the fundamental assumptions of the linear regression model). After this, a moving average helps to condense and highlight significant features in the data.

ARIMA is defined by three important parameters p, d, and q denoting the number of previous (older) observations to be considered for autoregression, and how many times the raw observations are differenced.

The equation below shows a typical autoregressive model. As the name suggests, the new values of this model depend only on a weighted linear combination of its past values. Since there are p past values, it is denoted as AR(*p*) or an autoregressive model of order p.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \epsilon_1 \quad (1)$$

The value of Y(t) is calculated based on the errors εt made by the previous model. Based on the window we are willing to look at in the past, the value of q is set. Thus, the above model can be denoted independently as moving average order q or simply MA(q).

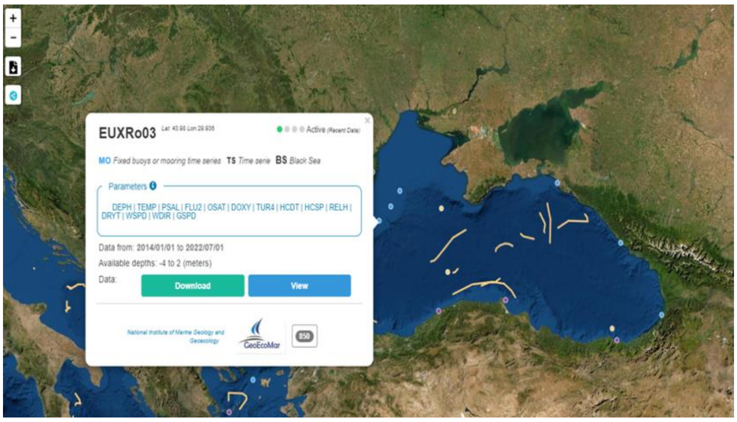
ARIMA has a combined autoregressive approach for modeling stationary time series data. This approach uncovers the significance of past fluctuations, includes overall trends, and deals with mitigating the effect of outliers or temporary abnormal changes in data. ARIMA is perfectly suited to capture historical trends, seasonality, randomness, and other non-static behaviors that people want.

To use the ARIMA model it is important to determine the parameters (p,d,q) - Best model: ARIMA intercept(1,0,3)(0,0,0)[0]. In the case of this work, the parameters used were 1,0,3 as the most optimal. Modeling of ocean currents is needed for a larger area so that machine learning can be a viable alternative to short-term predictions. Multivariate prediction models are a key point in predicting environmental time series leading to a wide range of application domains (from forecasting to anomaly detection). While such models are more difficult to implement using standard statistical models, Machine Learning technology enables a better model for such time series.

Using physical simulation to predict a wide range of trends in the atmospheric environment and data-driven algorithms to capture highly localized details improves forecasting capability [11].

Below is an example of Black Sea current modeling with ARIMA using data collected from surface geoscience that is maintained and managed by GeoEcoMar Constanța (Figure 2) [12]:Code: EUXRo03, Source: moored surface buoy, Institution: National Institute of Marine Geology and Geo-ecology (850), Last observation date:2022-07-01T15:00:00Z, Last latitude:43.98, Last longitude:29.936, NC files extracted from platform Copernicus [13]:

BS_TS_MO_EUXRo03_201701.nc; BS_TS_MO_EUXRo03_201702.nc;
BS_TS_MO_EUXRo03_201703.nc; BS_TS_MO_EUXRo03_201704.nc;
BS_TS_MO_EUXRo03_201705.nc; BS_TS_MO_EUXRo03_201706.nc;
BS_TS_MO_EUXRo03_201707.nc; BS_TS_MO_EUXRo03_201708.nc;
BS_TS_MO_EUXRo03_201709.nc; BS_TS_MO_EUXRo03_201710.nc;
BS_TS_MO_EUXRo03_201711.nc; BS_TS_MO_EUXRo03_201712.nc;
BS_TS_MO_EUXRo03_201801.nc; BS_TS_MO_EUXRo03_201802.nc;
BS_TS_MO_EUXRo03_201803.nc; BS_TS_MO_EUXRo03_201804.nc;
BS_TS_MO_EUXRo03_201805.nc; BS_TS_MO_EUXRo03_201806.nc;
BS_TS_MO_EUXRo03_201807.nc; BS_TS_MO_EUXRo03_201808.nc;
BS_TS_MO_EUXRo03_201809.nc; BS_TS_MO_EUXRo03_201810.nc;
BS_TS_MO_EUXRo03_201811.nc; BS_TS_MO_EUXRo03_201812.nc;
BS_TS_MO_EUXRo03_201901.nc; BS_TS_MO_EUXRo03_201903.nc;



BS_TS_MO_EUXRo03_201904.nc; BS_TS_MO_EUXRo03_201905.nc;
BS_TS_MO_EUXRo03_201906.nc; BS_TS_MO_EUXRo03_201907.nc;
BS_TS_MO_EUXRo03_201908.nc; BS_TS_MO_EUXRo03_201909.nc;
BS_TS_MO_EUXRo03_201910.nc; BS_TS_MO_EUXRo03_201912.nc;
BS_TS_MO_EUXRo03_202001.nc; BS_TS_MO_EUXRo03_202002.nc;
BS_TS_MO_EUXRo03_202003.nc; BS_TS_MO_EUXRo03_202004.nc;
BS_TS_MO_EUXRo03_202005.nc; BS_TS_MO_EUXRo03_202007.nc;
BS_TS_MO_EUXRo03_202008.nc; BS_TS_MO_EUXRo03_202009.nc;
BS_TS_MO_EUXRo03_202010.nc; BS_TS_MO_EUXRo03_202011.nc;
BS_TS_MO_EUXRo03_202012.nc; BS_TS_MO_EUXRo03_202101.nc;
BS_TS_MO_EUXRo03_202102.nc; BS_TS_MO_EUXRo03_202107.nc;
BS_TS_MO_EUXRo03_202108.nc; BS_TS_MO_EUXRo03_202109.nc;
BS_TS_MO_EUXRo03_202110.nc; BS_TS_MO_EUXRo03_202111.nc;
BS_TS_MO_EUXRo03_202112.nc; BS_TS_MO_EUXRo03_202201.nc;
BS_TS_MO_EUXRo03_202202.nc; BS_TS_MO_EUXRo03_202203.nc;
BS_TS_MO_EUXRo03_202204.nc; BS_TS_MO_EUXRo03_202205.nc.

Figure 3. Modeling the Black Sea currents [13]

Another example of the use of smart technologies in the maritime industry is the development by the Norwegian partners of the Marintech project of ship trajectory predictions in the encounter situation, based on a data framework, as shown in Figure 4. On the one hand, taking advantage of cluster methods, AIS data are clustered into similar groups. patterns, or called routes. The idea is to use the historical routes to predict the ship's trajectory, given the current state of the ship's motion [15]. On the other hand, we extract ship encounter situations from AIS data. Expert knowledge about encounter types, including head-on situations, overtaking, and crossing situations, are analyzed and modeled as classifiers for encounter detection [16]. As a result, route group route inputs and encounter detection could improve the performance of vessel trajectory prediction, thereby improving the safety of navigation in crowded waters. Oslofjord, Norway has been selected as the AIS data and testing area in 2019-2020 for the proposed scheme. Some preliminary results have been published in international conferences, and more efforts are now being made to investigate ship motion prediction in more complicated encounters, such as multi-ship encounters.

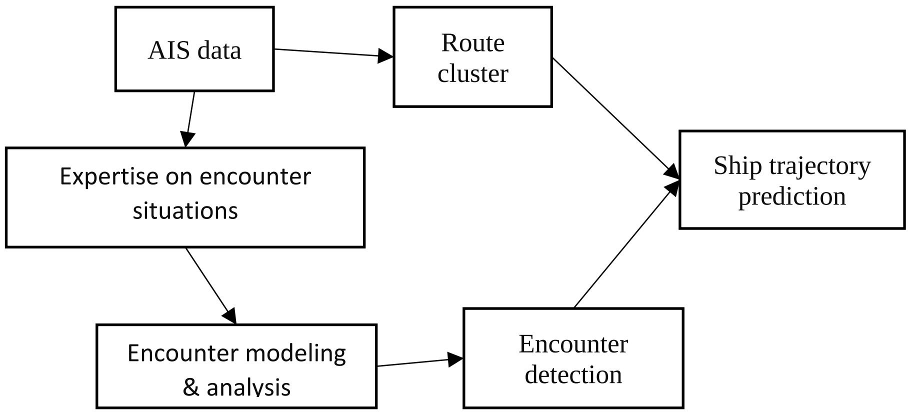


Figure 4. Scheme for ship trajectory prediction in close-range encounters

Conclusions

Oceanography and bathymetry are essential to understanding and exploiting the marine environment in an efficient and responsible manner. The accuracy of data collection and interpretation through intelligent technologies used in these fields contributes, within the maritime industry, to the improvement of safety, navigation, and environmental protection, as well as to the exploration and exploitation of marine resources in a more environmentally sustainable way.

Data analysis and modeling based on machine learning and artificial intelligence in oceanography and bathymetry help improve our understanding of the oceans and prevent negative impacts on the environment and marine life. To achieve this we need an accurate and up-to-date database. It is therefore important to invest in smart technologies to collect and store relevant data, such as autonomous underwater vehicles and robots equipped with smart sensors (IoT), sonars, and high-resolution cameras, as well as data transmission and collection equipment.

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This article presents the achievements of the Romanian-Norwegian team in the MARINTECH project, ”Romanian – Norwegian Strategic Cooperation in Maritime Higher Education for the Enhancement of human capital and knowledge base in the Field of marine intelligent technologies”.

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