

NEURAL NETWORK ESTIMATION OF A DISTANCE TO A MARINE OBJECT USING CAMERA

TECHNICAL FIELD

The presently disclosed subject matter relates to the field of marine environment.

BACKGROUND

In a marine environment, a marine vessel travels on a route on which it can encounter various situations. Some of these situations can include dangers, e.g., an obstacle to be avoided, zones with dangerous weather, etc.

In order to enable control of the marine vessel (by the crew and/or by an automatic pilot), it is required to determine information on marine objects encountered by the marine vessel.

It is now necessary to provide new methods and systems in order to improve safety and reliability of marine vessels navigation, improve understanding of the marine environment for marine vessels, and improve control of marine vessels. More generally, it is necessary to develop innovative methods in the marine domain, and in particular, in the field of autonomous ships.

GENERAL DESCRIPTION

In accordance with certain aspects of the presently disclosed subject matter, there is provided a system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to implement at least one neural network, wherein the PMC is configured to obtain at least one image of a marine object, acquired by an imaging device of a marine vessel, feed the image to the at least one neural network, and use the at least one neural network to estimate a distance between the marine vessel and the marine object.

In addition to the above features, the system according to this aspect of the presently disclosed subject matter can optionally comprise one or more of features (i) to (xvii) below, in any technically possible combination or permutation:

- i. the system is configured to obtain at least one image of a marine object, acquired by an imaging device of a marine vessel, obtain data D_{height}

- informative of a height of the imaging device at a period of time at which the image has been acquired, feed the image and the data D_{height} to the at least one neural network, and use the at least one neural network to estimate a distance between the marine vessel and the marine object;
- ii. the system is configured to use the at least one neural network to determine, using said image, a plurality of different candidate distances between the marine vessel and the marine object;
 - iii. the system is configured to obtain a plurality of images of a marine object, acquired by the imaging device of the marine vessel at different instants of time of a given period of time, feed each image of the plurality of images to the at least one neural network, use the at least one neural network to estimate, for each image of the plurality of images, one or more candidate distances between the marine vessel and the marine object, thereby obtaining, based on the plurality of images, a set of candidate distances for the given period of time, and use the set of candidate distances to estimate a distance between the marine vessel and the marine object within the given period of time;
 - iv. the system is configured to determine data $D_{\text{distribution}}$ informative of a frequency distribution of the candidate distances within the set of candidate distances, and use the frequency distribution to estimate a distance between the marine vessel and the marine object;
 - v. the system is configured to obtain data D_{physical} informative of an expected motion of the marine object, and use data D_{physical} to estimate a distance between the marine vessel and the marine object;
 - vi. the system is configured to obtain a plurality of images of a marine object, acquired by the imaging device of the marine vessel at different instants of time of a given period of time, feed each image of the plurality of images to the at least one neural network, use the at least one neural network to estimate, for each image of the plurality of images, one or more candidate distances between the marine vessel and the marine object, thereby obtaining, based on the plurality of images, a set of candidate distances for the given period of time, and use data D_{physical} to determine whether at least one candidate distance of the set of candidate distances is not acceptable

as an estimate of a distance between the marine vessel and the marine object;

- vii. the system is configured to obtain at least one image of a marine object, acquired by an imaging device of a marine vessel, feed the image to the at least one neural network, use the at least one neural network to determine a distribution including a plurality of candidate distances, each candidate distance being associated with a probability, upon detection that the distribution does not meet a criterion, generate data which indicates that the at least one neural network has to be retrained;
- viii. the system is configured to determine that a distance estimation performed by the at least one neural network does not meet a quality criterion for one or more given images of one or more marine objects acquired by the imaging device which correspond to a same given scenario;
- ix. the system is configured to retrain the at least one neural network with a training set of images that match the given scenario;
- x. the system is configured to identify the given scenario using data associated with the given images, the data including at least one of (a) or (b) or (c) or (d) or (e): (a) a type of the one or more marine objects, (b) data informative of an environment in which the given images have been acquired, (c) a range of distances in which at which the or more marine objects are located, (d) data informative of an orientation of the one or more marine objects as displayed in the given images, (e) a range of heights of the imaging device, for which the given images have been acquired;
- xi. the system is configured to obtain at least one image of a marine object, acquired by the imaging device of the marine vessel, obtain data $D_{\text{environmental}}$ informative of an environment in which the image has been acquired, feed the image and data $D_{\text{environmental}}$ to the at least one neural network, and use the at least one neural network to estimate a distance between the marine vessel and the marine object;
- xii. the system configured to provide the distance to a controller of the marine vessel, wherein the controller is operative to control a trajectory of the marine vessel using the distance;

- xiii. the system is configured to obtain one or more images of a marine object, feed the one or more images to the at least one neural network, and use the at least one neural network to estimate a distance between the marine vessel and the marine object, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel;
- xiv. the system is configured to estimate, by the at least one neural network, a distance between the marine vessel and the marine object using an image of the marine object acquired by the imaging device of the marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device;
- xv. the at least one neural network has been trained using a set of images and labelled data, each given image of the set of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data comprises, for each given image, an estimate of a distance between the given marine vessel and the given marine object, and an estimate of a height of the imaging device at a period of time at which the given image has been acquired;
- xvi. the system is configured to obtain at least one image of a marine object, acquired by the imaging device of the marine vessel, obtain data $D_{\text{orientation}}$ informative of an orientation of the imaging device at a period of time at which the image has been acquired, feed the image and the data $D_{\text{orientation}}$ to the at least one neural network, and use the at least one neural network to estimate a distance between the marine vessel and the marine object; and
- xvii. the neural network has been trained using a set of images and labelled data, each given image of the set of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data comprises, for each given image, an estimate of a distance between the given marine vessel and the given marine object, wherein the labelled data further comprises, for at least one given image, data informative of an orientation of the given marine object as displayed in the given image.

In accordance with certain aspects of the presently disclosed subject matter, there is provided a system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to implement at least one neural network, wherein the PMC is configured to obtain a plurality of images, each given image of the plurality of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein each given image is associated with a given label indicative of a distance between the given marine vessel and the given marine object, feed each given image of the plurality of images together with the given label to the at least one neural network to train the at least one neural network, wherein the at least one neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of the marine vessel.

In addition to the above features, the system according to this aspect of the presently disclosed subject matter can optionally comprise one or more of features (xviii) to (xxiv) below, in any technically possible combination or permutation:

- xviii. the system is configured to, for each given image of the plurality of images, obtain data D_{height} informative of a height of the given imaging device at a period of time at which the given image has been acquired, and feed the given image and the data D_{height} to the at least one neural network for its training;
- xix. the system is configured to, for a given image of the plurality of images, obtain the given label indicative of a distance between the given marine vessel and the given marine object using data provided by at least one of (a) a sensor of the given marine vessel different from the imaging device, or (b) a sensor of the given marine object;
- xx. the system is configured to obtain first position data informative of a position of first marine objects, wherein the first position data is obtained based on the given image acquired by the given imaging device of the given marine vessel, obtain second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, determine that a marine object of the

first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor, and determine the given label indicative of the given distance between the given marine vessel and the given marine object using data provided by the at least one sensor;

- xxi. the system is configured to, for a given image of the plurality of images:
 - (a) obtain data $D_{\text{environmental}}$ informative of an environment in which the given image has been acquired, and feed the given image and the data $D_{\text{environmental}}$ to the neural network for its training, or (b) obtain data $D_{\text{orientation}}$ data informative of an orientation of the given marine object as displayed in the given image, and feed the given image and the data $D_{\text{orientation}}$ to the at least one neural network for its training;
- xxii. the system is configured, for a given scenario in which a given image of a given marine object is acquired by the imaging device, to determine that an estimation of the distance by the neural network does not meet a quality criterion, and retrain the neural network with a training set of images matching the given scenario;
- xxiii. the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of a marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device; and
- xxiv. the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using one or more images of a marine object acquired by an imaging device of a marine vessel, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel.

In accordance with certain aspects of the presently disclosed subject matter, there is provided a system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to obtain first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device of a given marine vessel, obtain second position

data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and determine that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor, determine a given distance between the given marine vessel and the given marine object using data provided by the at least one sensor, and generate a labelled image, wherein the labelled image comprises the given image and a label comprising said given distance.

In addition to the above features, the system according to this aspect of the presently disclosed subject matter can optionally comprise one or more of features (xxv) to (xxvii) below, in any technically possible combination or permutation:

- xxv. the system is configured to determine data D_{camera} informative of at least one of a height and an orientation of the imaging device at a period of time at which the given image has been acquired by the imaging device, which optimize a matching between: position of at least some of the first marine objects determined using D_{camera} and the first position data, and second position data of at least some of the second marine objects, according to a criterion;
- xxvi. the system is configured to determine a type of the given marine vessel using data provided by the at least one sensor, and associate the type with the labelled image; and
- xxvii. the at least one sensor is not an imaging device, and/or the at least one sensor includes at least one of a radar and an automatic identification system (AIS) and/or the at least one sensor includes a first sensor and a second sensor, wherein the second sensor is of a different type than the first sensor, and wherein the first sensor and the second sensor are not imaging devices.

In accordance with certain aspects of the presently disclosed subject matter, there is provided a method comprising, by a processor and memory circuitry (PMC) implementing at least one neural network, obtaining at least one image of a marine object, acquired by an imaging device of a marine vessel, feeding the image to the at least one

neural network, and using the at least one neural network to estimate a distance between the marine vessel and the marine object.

In addition to the above features, the method according to this aspect of the presently disclosed subject matter can optionally implement one or more of features (i) to (xvii) above (described with reference to the corresponding system), in any technically possible combination or permutation:

In accordance with certain aspects of the presently disclosed subject matter, there is provided a non-transitory storage device readable by a machine, tangibly embodying a program of instructions executable by the machine to perform operations as described with reference to the method above.

In accordance with certain aspects of the presently disclosed subject matter, there is provided a method comprising, by a processor and memory circuitry (PMC) implementing at least one neural network, obtaining a plurality of images, each given image of the plurality of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein each given image is associated with a given label indicative of a distance between the given marine vessel and the given marine object, feeding each given image of the plurality of images together with the given label to the neural network to train the at least one neural network, wherein the at least one neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of the marine vessel.

In addition to the above features, the method according to this aspect of the presently disclosed subject matter can optionally implement one or more of features (xviii) to (xxiv) above (described with reference to the corresponding system), in any technically possible combination or permutation:

In accordance with certain aspects of the presently disclosed subject matter, there is provided a non-transitory storage device readable by a machine, tangibly embodying a program of instructions executable by the machine to perform operations as described with reference to the method above.

In accordance with certain aspects of the presently disclosed subject matter, there is provided a method comprising, by a processor and memory circuitry (PMC), obtaining first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device of a given marine vessel, obtaining second position data informative of a position of

second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and determining that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor, determining a given distance between the given marine vessel and the given marine object using data provided by the at least one sensor, and generating a labelled image, wherein the labelled image comprises the given image and a label comprising said given distance.

In addition to the above features, the method according to this aspect of the presently disclosed subject matter can optionally implement one or more of features (xxv) to (xxvii) above (described with reference to the corresponding system), in any technically possible combination or permutation:

In accordance with certain aspects of the presently disclosed subject matter, there is provided a non-transitory storage device readable by a machine, tangibly embodying a program of instructions executable by the machine to perform operations as described with reference to the method above.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object in an accurate and efficient way.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object using a single camera.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object in real time, or quasi real time.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object using multiple cameras.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object using only images acquired by a camera, without requiring input from other sensors.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object using an image acquired by a camera, even if a representation of the marine object in the image has a limited size.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object using an image acquired by a

camera, while being substantially insensitive to motion of the camera and/or to motion of the marine vessel due to the presence of waves.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object, even at long distances.

According to some embodiments, the proposed solution enables estimation of a distance between a marine vessel and a marine object while taking into consideration environmental conditions.

According to some embodiments, the proposed solution can be easily deployed on a marine vessel.

According to some embodiments, the proposed solution generates, automatically, a dataset of labelled images of marine objects, usable for training a neural network, to determine distance to a marine object using an image thereof.

According to some embodiments, the proposed solution is able to assess in which context the neural network is less efficient to predict the distance to the marine object, in order to retrain the neural network with a training set which focuses on this context.

According to some embodiments, the proposed solution enables accurate and efficient estimation of a distance in the maritime domain, which is a challenging technical domain, since it can involve bad environmental conditions, variations of the height of the marine vessel over time, etc. To the contrary, standard methods for distance estimation (such as triangulation and stereovision) cannot be used and would be both inaccurate and impractical in the marine domain.

BRIEF DESCRIPTION OF THE DRAWINGS

In order to understand the invention and to see how it can be carried out in practice, embodiments will be described, by way of non-limiting examples, with reference to the accompanying drawings, in which:

- **Fig. 1** illustrates an embodiment of a system which can be used to perform one or more of the methods described hereinafter;
- **Fig. 2A** illustrates an embodiment of a method of determining a distance to a marine object using an image acquired by an imaging device of a marine vessel;

- **Fig. 2B** illustrates an example of an image of a marine object acquired by the imaging device of a marine vessel;
- **Fig. 2C** illustrates a schematic representation of a distance between a marine vessel and a marine object;
- **Fig. 2D** illustrates a schematic representation of the influence of the height of the imaging device in estimating the distance between the marine vessel and the marine object;
- **Fig. 2E** illustrates an example of a distribution of candidate distances estimated by a neural network;
- **Fig. 3A** illustrates an embodiment of a method of determining a distance to a marine object using a plurality of images acquired by an imaging device of a marine vessel;
- **Fig. 3B** illustrates an example of a plurality of distributions of candidate distances estimated by a neural network over time;
- **Fig. 3C** illustrates an embodiment of a system which uses the plurality of distributions of candidate distances estimated by a neural network over time to determine the candidate distance;
- **Fig. 3D** illustrates an embodiment of a method of determining a frequency distribution within a set of candidate distances to estimate the candidate distance;
- **Fig. 4** illustrates an embodiment of a method of training a neural network to estimate a distance to a marine object using an image acquired by an imaging device of a marine vessel;
- **Fig. 5** illustrates an impact of the orientation of the marine object at sea on its representation in the image;
- **Fig. 6A** illustrates an embodiment of a method of assessing performance of the trained neural network;
- **Fig. 6B** illustrates an example of a distribution of candidate distances output by the trained neural network, which indicates that the performance of the trained neural network does not meet a quality criterion;
- **Fig. 7** illustrates an embodiment of a method of determining data informative of a height and/or orientation of an imaging device of a marine vessel;
- **Fig. 7A** illustrates a variant of the method of **Fig. 7**;

- **Fig. 7B** illustrates an example of tracking marine objects over a plurality of images acquired by an imaging device of a marine vessel;
- **Fig. 7C** illustrates a method of determining data informative of a height and/or orientation of an imaging device of a marine vessel over time;
- **Fig. 7D** illustrates operations which can be performed in accordance with the method of **Fig. 7**;
- **Fig. 7E** illustrates schematically a projection of the position of the marine objects acquired by the imaging device and the position of the marine objects acquired by another sensor into a common referential;
- **Fig. 7F** illustrates an embodiment of a method of projecting position of a marine object from the image to a global/absolute referential (independent of the image);
- **Figs. 7G to 7J** illustrate parameters that can be used in the method of **Fig. 7F**;
- **Fig. 7K** illustrates an example of an output of the method of **Fig. 7D**;
- **Fig. 7L** illustrates operations which can be performed in accordance with the method of **Fig. 7A**;
- **Figs. 7M and 7N** illustrate an embodiment of using tracking data of marine objects to improve solving of an optimization problem in the method of **Fig. 7L**;
- **Figs. 8A and 8B** illustrate an embodiment of using types of marine objects to improve solving of an optimization problem in the methods of **Figs. 7D and 7L**;
- **Fig. 9A** illustrates an embodiment of the method of **Fig. 7**;
- **Fig. 9B** illustrates another embodiment of the method of **Fig. 7**; and
- **Fig. 10** illustrates an embodiment of a method of generating, automatically, a labelled image of a marine object, which is associated with the distance to the marine object.

DETAILED DESCRIPTION

In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of the invention. However, it will be understood by those skilled in the art that the presently disclosed subject matter may be practiced without these specific details. In other instances, well-known methods have not been described in detail so as not to obscure the presently disclosed subject matter.

Unless specifically stated otherwise, as apparent from the following discussions, it is appreciated that throughout the specification, discussions utilizing terms such as “obtaining”, “using”, “feeding”, “determining”, “estimating”, “generating” or the like, refer to the action(s) and/or process(es) of a computer that manipulate and/or transform data into other data, said data represented as physical, such as electronic, quantities and/or said data representing the physical objects.

The terms “computer” or “computerized system” should be expansively construed to include any kind of hardware-based electronic device with a data processing circuitry (e.g., digital signal processor (DSP), a GPU, a TPU, a field programmable gate array (FPGA), an application specific integrated circuit (ASIC), microcontroller, microprocessor etc.). The processing circuitry can comprise, for example, one or more processors operatively connected to computer memory, loaded with executable instructions for executing operations, as further described below. The processing circuitry encompasses a single processor or multiple processors, which may be located in the same geographical zone or may, at least partially, be located in different zones, and may be able to communicate together.

Fig. 1 illustrates an embodiment of a computerized system **100** which can be used to perform one or more of the methods described hereinafter. As shown, system **100** comprises a processor and memory circuitry (PMC) **110**.

System **100** can be embedded on a marine platform. In particular, the marine platform can be a moving marine platform. The moving marine platform can be e.g., a marine vessel **125**. Marine vessels include e.g., ships, boats, hovercrafts, etc.

In some embodiments, system **100** can be embedded on a marine platform which can be stationary, or at least temporarily stationary.

Although embodiments will be described with reference to marine vessels **125**, it is to be understood that these embodiments apply similarly to a stationary marine platform.

As shown in **Fig. 1**, system **100** can obtain data from one or more sensors **130**. At least some of the sensors **130** can be located on the marine vessel **125** on which system **100** is located (or on at least one other marine vessel/object communicating with the marine vessel **125** on which system **100** is located).

Sensors **130** collect data during the voyage of the marine vessel **125**. The voyage includes portions of the voyage in which the marine vessel is in motion, but can also

include portions of the voyage in which the marine vessel is substantially static (e.g., when the marine vessel **125** is moored or docked, such as in a harbor).

Sensors **130** include an imaging device **120** (e.g. a camera), which is mounted on the marine vessel **125**.

In some embodiments, the camera includes an infrared camera, a night camera, a day camera, etc.

In some embodiments, sensors **130** include a plurality of imaging devices **120** (which can be distinct). In some embodiments, the imaging devices **120** may have different fields of view (which do not overlap at all), or may have a field of view which can at least partially overlap.

According to some embodiments, sensors **130** include one or more additional sensors **115** (which are not necessarily imaging devices) such as (this list is not limitative) a radar (any type of radar), a LIDAR, an automatic identification system (AIS) (located on the marine vessel **125** and/or on a marine object distinct from the marine vessel **125**), a transponder communicating with a GPS located on other marine objects, a system which includes a laser located on the marine vessel **125**, and an optical reflector located on another marine object to be located by the marine vessel **125** (reflection of the laser by the reflector enables localization of the other marine object), etc.

In particular, sensors **115** provide information usable to localize marine objects surrounding the marine vessel **125**.

The marine vessel **125** itself can include other sensors, such a geo-localization system (e.g., GPS), IMU, velocity and acceleration sensors, a gyro compass, etc.

As explained hereinafter in the specification, system **100** can process data collected by one or more of the sensors **130**.

In some embodiments, data output by system **100** can be transmitted through a remote communication network **140** towards e.g., a central station **150**, which can include at least one processor and memory circuitry (PMC).

In some embodiments, the central station **150** can perform at least some of the tasks of PMC **110** located on the marine vessel **125**.

The remote communication link can correspond e.g. to a broadband cellular network (e.g. 4G, 5G, LTE, etc.), a satellite communication network, radio communication network (such as Radio VHF – very high frequency), etc.

Data can be transmitted using a communication system located on the marine vessel **125** which is suitable to transmit data via the remote communication network. The communication system can include e.g., an antenna, an emitter, a transponder, etc.

As visible in **Fig. 1**, the processor of PMC **110** can be configured to implement a neural network (NN) **160**. In some embodiments, the neural network **160** can be a deep neural network.

In particular, the processor can execute several computer-readable instructions implemented on a computer-readable memory comprised in the PMC, wherein execution of the computer-readable instructions enables data processing by the neural network. As explained hereinafter, NN **160** enables data processing of one or more images of one or more marine objects, for outputting distance information of the one or more marine objects.

By way of non-limiting example, the layers of NN **160** can be organized in accordance with Convolutional Neural Network (CNN) architecture, Recurrent Neural Network architecture, Recursive Neural Networks architecture, Generative Adversarial Network (GAN) architecture, or otherwise. In some embodiments, at least some of the layers can be organized in a plurality of DNN sub-networks. Each layer of the DNN can include multiple basic computational elements (CE), typically referred to in the art as dimensions, neurons, or nodes.

Generally, computational elements of a given layer can be connected with CEs of a preceding layer and/or a subsequent layer. Each connection between a CE of a preceding layer and a CE of a subsequent layer is associated with a weighting value. A given CE can receive inputs from CEs of a previous layer via the respective connections, each given connection being associated with a weighting value which can be applied to the input of the given connection. The weighting values can determine the relative strength of the connections and thus the relative influence of the respective inputs on the output of the given CE. The given CE can be configured to compute an activation value (e.g., the weighted sum of the inputs) and further derive an output by applying an activation function to the computed activation. The activation function can be, for example, an identity function, a deterministic function (e.g., linear, sigmoid, threshold, or the like), a stochastic function, or other suitable function. The output from the given CE can be transmitted to CEs of a subsequent layer via the respective connections. Likewise, as above, each connection at the output of a CE can be associated with a weighting value which can be applied to the output of the CE prior to

being received as an input of a CE of a subsequent layer. Further to the weighting values, there can be threshold values (including limiting functions) associated with the connections and CEs.

System **100** can be used to perform one or more of the methods described hereinafter.

Attention is now drawn to **Fig. 2A**.

The method includes obtaining (operation **200**) at least one image of a marine object, acquired by an imaging device **120** of a marine vessel **125**.

In some embodiments, the image can include a plurality of different marine objects.

The marine objects can include e.g., other marine vessels, icebergs, buoys, etc. The marine objects generally include at least a part which is located above sea level.

A non-limitative example of an image **280** is illustrated in **Fig. 2B**, in which an imaging device (not visible in **Fig. 2B**) mounted on the marine vessel **125** has acquired an image of the marine object **270**.

The method further includes feeding (operation **210**) the image to the neural network **160**.

According to some embodiments, the image is pre-processed before being fed to the neural network **160**. In particular, a PMC (such as PMC **110**) can execute an algorithm which is configured to detect, in the image acquired by the imaging device **120**, marine objects present in the image.

This detection can rely e.g., on an image processing algorithm. In some embodiments, a machine learning module **159** (which implements e.g., a neural network, such as a deep neural network) is trained to detect marine objects present in images acquired by an imaging device of a marine vessel. In some embodiments, the machine learning network implemented in the machine learning module **159** can be distinct from the neural network **160**, but this is not mandatory.

This training can include supervised learning in which a plurality of annotated images comprising marine objects are fed to the machine learning module. Each annotated image can include e.g., a bounding box provided by an operator who indicates the location of the marine object(s) in the image.

This is not limitative, and the training can also include automatic training and/or non-supervised learning.

In some embodiments, the machine learning module **159** can provide information on the type of the object (e.g., marine vessel, type of marine vessel, type of marine object such as an iceberg, etc.). This can be obtained by performing supervised learning of the machine learning module, in which labelled images comprising marine objects (together with their type, which corresponds to the label) are fed to the machine learning module **159** for its training.

The output of the identification of the marine object(s) in the image can include a geometric representation (e.g., a bounding box) indicative of the estimated location of each marine object(s) in the image. A non-limitative example is provided in **Fig. 2B**, in which the bounding box **275** surrounds the marine vessel **270** in the image **280**.

In some embodiments, the neural network **160** can be trained to identify, by itself, the marine object(s) in the image(s) received from the imaging device **120** (or from another imaging device).

As visible in **Fig. 2A**, the method further includes using (operation **220**) the neural network **160** to estimate a distance between the marine vessel **125** and the marine object. An example of such a distance is depicted in **Fig. 2C**, which corresponds to the distance **276** between the marine vessel **125** and the marine object **270** (the distance can be expressed e.g., along a horizontal direction with a constant altitude, as depicted in **Fig. 2C** – this is however not limitative). If the sea level is considered as the X-Y plane, and the Z axis corresponds to the height from the sea level, the distance can be expressed e.g. between a point of the sea level located at the same X/Y coordinates as the imaging device **120** of the marine vessel **125** and the marine object **270**. This is not limitative, and other conventions can be used.

In some embodiments, the distance is estimated from the marine vessel **125** and the centre of the geometric representation (e.g., bounding box) surrounding the marine object **270** in the image(s).

As explained hereinafter, the neural network **160** has been previously trained to be able to output, based on an image of a marine object, the estimated distance between a marine vessel (on which an imaging device acquiring the image is located) and the marine object.

According to some embodiments, the neural network **160** provides, in real time, or quasi real time after obtaining the image from the imaging device **120**, an estimation of the distance between the marine vessel **125** and the marine object.

The distance determined by the neural network **160** can be output to a user (using e.g., a display device such as a screen) and/or can be provided to another system, such as an auto-pilot system of the marine vessel **125**, which controls the trajectory of the marine vessel **125** over time using *inter alia* the estimated distance. The auto-pilot system can generate commands for actuators (e.g., motor(s), rudder(s)) to control the trajectory of the marine vessel **125**. For example, if the distance to the marine object is below a threshold (which indicates that a collision may occur), the auto-pilot system can send a command to the actuators of the marine vessel **125** to change its trajectory, thereby avoiding a collision. This example is not limitative.

According to some embodiments, the neural network **160** is fed (in addition to the image of the marine object acquired by the imaging device **120** of the marine vessel **125**) with data D_{camera} informative of an orientation and/or of a height of the imaging device **120** within a period of time during which the image has been acquired (operation **230**).

The neural network **160** can take into account data D_{camera} to provide an estimation of the distance to the marine object.

This additional input can, in some embodiments, improve accuracy of the estimation of the distance between the marine vessel **125** and the marine object.

Fig. 2B illustrates an example in which the height of the imaging device **120** impacts the display of the marine object in the image.

In the two images of **Fig. 2B**, the distance **276** to the marine object **270** is the same. However, the height of the imaging device **120** is not the same. In the bottom part of **Fig. 2D**, the imaging device **120** is mounted on a ship **126** which is of greater size than the ship **125** illustrated in the upper part of **Fig. 2D**. Therefore, the height H_2 of the imaging device **120** on the ship **126** is larger than the height H_1 of the imaging device **120** on the ship **125**.

This causes the same marine object **270** (located at the same distance) to appear differently in the images acquired by the imaging device **120**, and can impact distance estimation, since distance estimation relies on the images of the imaging device **120**.

In some embodiments, the neural network **160** can be fed with the height (and/or orientation) of the imaging device **120** within a period of time at which the image has been acquired, in order to prevent the height of the imaging device **120** to alter the distance estimation.

As explained hereinafter, in some embodiments, the estimated height (and/or orientation) can be fed to the neural network **160** during training of the neural network **160**. The neural network **160** can therefore learn to predict the distance to the marine object

although the height of the imaging device (and in turn the representation of the marine object in the images) can vary.

In some embodiments, the estimated height (and/or orientation) can be fed to the neural network **160** during the prediction phase (in which the neural network **160** estimates the distance to the marine object based on one or more images thereof).

Note that the height of the imaging device **120** can also vary over time for a given marine vessel, due to the variations in the wave height at sea, a change of the freight of the marine vessel, a change in the number of passengers of the marine vessel, etc. Estimation of the height of the imaging device **120** can be performed and can be used (as an input of the neural network **160**) to prevent the change(s) in the height from altering the distance estimation.

In some embodiments, for each image acquired at time T , the corresponding estimation of the height (and/or orientation) of the imaging device **120** at time T (or at time T_1 close to T if there is a processing delay) is fed to the neural network **160**.

Embodiments for determining D_{camera} (which includes height and/or orientation of the imaging device) will be provided hereinafter.

According to some embodiments, the neural network **160** is fed (in addition to the image of the marine object acquired by the imaging device **120** of the marine vessel **125**) with data $D_{\text{environmental}}$ informative of the environment in which the image has been acquired (see operation **240**).

The neural network **160** can take into account data $D_{\text{environmental}}$ to provide an estimation of the distance to the marine object.

This additional input can, in some embodiments, improve accuracy of the estimation of the distance between the marine vessel **125** and the marine object.

$D_{\text{environmental}}$ can include e.g., data informative of the environmental conditions, e.g. whether it is day or night, and meteorological conditions (clear sky, foggy, cloudy, rainy, etc.).

$D_{\text{environmental}}$ can include data characterizing the environment in which the image has been acquired (e.g., whether the image has been acquired at a port, in a canal, near the shore, or at a far shore, etc.).

$D_{\text{environmental}}$ can be obtained using e.g., sensors of the marine vessel **125** and/or by data provided by third parties. For example, meteorological conditions can be measured using temperature sensor, pressure sensor, or can be provided by a third party. Data informative of the type of environment encountered by the marine vessel **125** can be

determined using e.g., position of the marine vessel **125** (e.g., using GPS/AIS) and a map indicative of the type of environment at sea (which maps position of ports, etc.). These examples are not limitative.

Note that the environment in which the image has been acquired (such as the meteorological conditions) affect the estimation process of the distance. Indeed, the visibility of the marine object in the images is not the same depending on the environmental conditions. It is more challenging to determine the distance to the marine object at low visibility (e.g., at night and/or in presence of fog) than at high visibility (e.g. during day time in open sea). Usage of the data $D_{\text{environmental}}$ (in prediction and/or during training) is helpful to enable the neural network **160** to estimate the distance to the marine object even in difficult environmental conditions.

According to some embodiments, the neural network **160** can determine, for a given image, a plurality of candidate distances between the marine vessel **125** and the marine object. For each candidate distance, the neural network **160** can provide a probability that the candidate distance is a correct estimate of the distance between the marine vessel and the marine object.

A non-limitative example is depicted in **Fig. 2E**, in which, for each candidate distance (the X-axis of the graph corresponds to the estimation of the distance value D between the marine vessel **125** and the marine object), a probability (the Y-axis of the graph corresponds to the probability P associated with each distance value) is provided. The higher the value of P , the higher the probability that the corresponding distance value is correct according to the neural network **160**.

In some embodiments, the distance output by the neural network **160** can be selected as the candidate distance with the highest probability. This is not limitative. In some embodiments, a statistical analysis can be performed on the probability distribution of the candidate distances. The statistical analysis includes e.g., one sigma, two sigma, etc. (or other statistical methods).

Note that the method of **Fig. 2A** can be performed in parallel for a plurality of different marine objects. Assume for example that a plurality of N different marine objects is present in the image. The pixel position of each marine object can be identified in the image (as explained above). The image (together with the position of each marine object in the image) can be fed to the neural network **160** which outputs, for each given marine object, an estimate of the distance from the marine vessel **125** to the given marine object.

According to some embodiments, it is possible to feed additional data to the neural network **160** to enable distance estimation, such as the type of the marine object. The type of the marine object can be deduced from the image using image processing algorithms, or using information provided by another sensor.

As can be understood from the method of **Fig. 2A**, according to some embodiments, it is possible to determine the distance to the marine object using data acquired by the imaging device, without using data informative of the marine object acquired by a sensor (e.g., AIS, radar, etc.) different from the imaging device. In some embodiments, the distance to the marine object can be determined using only data acquired by the imaging device.

According to some embodiments, the neural network **160** is fed with one or more images of a given marine object. All of the one or more images provided to the neural network **160** have been acquired by the same single imaging device of the marine vessel (note that this does not preclude the marine vessel to embed other imaging devices) and the neural network **160** determines the distance to the marine object using these images. In other words, this enables to determine distance to the marine object using a single camera of a marine vessel.

Attention is now drawn to **Fig. 3A**.

The method of **Fig. 3A** includes obtaining (operation **300**) a plurality of images (a sequence of images) of a marine object, acquired by the imaging device at different periods of time.

The method further includes feeding (operation **310**) each image of the plurality of images to the neural network **160**. The images can be e.g., fed sequentially to the neural network **160**, one after the other. Alternatively, they can be fed simultaneously to the neural network **160**.

According to some embodiments, the time interval between the acquisition of the first image and acquisition of the last image of the sequence of images is below a threshold. For example, the first image is acquired at time T_1 , the second image is acquired at time $T_2 > T_1$, and the last image is acquired at time T_N , with $|T_N - T_1| < threshold$.

In some embodiments, the threshold can be chosen such as the displacement of the marine object with respect to the marine vessel **125** between the different images is negligible. In this case, the threshold depends on the relative position of the marine object. If the marine object is located near the horizon line, the threshold can be up to one minute,

and if the marine object is located close to the bottom of the image, the threshold can be up to one second. Note that these values are not limitative.

As explained above, the marine object can be identified in each image using for example the machine learning module **159**. A tracking method can be used to track the marine object over the different images. The tracking method can be implemented by a PMC, such as PMC **110**. The tracking method can use e.g., a Kalman filter, or other adapted tracking methods can be used. The tracking method enables to understand the motion of each marine object over the plurality of images.

The method further includes using (operation **320**) the neural network **160** to estimate, for each image of the plurality of images, one or more candidate distances between the marine vessel **125** and the marine object. Since this operation is repeated for each image (acquired at different periods of time), a set of candidate distances over time is obtained.

For example, as illustrated in **Fig. 3B**, for the image of the marine object **370** acquired at T_1 , the distribution **375** of candidate distances is obtained (each candidate distance being associated with a probability), for the image of the marine object **370** acquired at T_2 , the distribution **376** of candidate distances is obtained (each candidate distance being associated with a probability), and for the image of the marine object **370** acquired at T_N , the distribution **377** of candidate distances is obtained.

The set **380** of candidate distances is therefore obtained (which can include all or at least part of the candidate distances determined in the given period of time ($[T_1; T_N]$)). The set **380** of candidate distances can be used to estimate a distance between the marine vessel and the marine object within the given period of time ($[T_1; T_N]$).

In some embodiments, the set **380** of candidate distances can include e.g., only the candidate distances of the distributions **375**, **376** and **377** which have a probability higher than a threshold. This is however not limitative, and the set **380** of candidate distances can include all candidate distances of the various distributions **375**, **376** and **377**.

In some embodiments, a state estimator **385** implemented by the PMC **110**, such as a Kalman filter, a deep neural network, a high pass or low pass filter, can be fed with the set **380** of candidate distances. The state estimator **385** can use the set **380** of candidate distances to output an estimate **390** of the distance between the marine vessel **125** and the marine object within the given period of time ($[T_1; T_N]$). The state estimator **385** can for example smoothen the distance estimation over time (e.g., by filtering sudden variations in the distance estimation).

In other embodiments, the neural network **160** is operative to handle time series data. For example, a recurrent neural network, a LSTM (Long short-term memory (LSTM)), or other adapted neural networks can be used to determine distance to the marine object over time, using the sequence of images acquired at different periods of time.

According to some embodiments, the method includes determining (operation **391** in **Fig. 3D**) data $D_{\text{distribution}}$ informative of a frequency distribution of the candidate distances within the set **380** of candidate distances. Indeed, each candidate distance D_i can be present M_i times (with M_i equal to or greater than one) within the set **380** of candidate distances. For example, assume that the neural network **160** has estimated that the distance between the marine vessel and the given marine object is D_1 at time T_1 , and that the distance between the marine vessel and the given marine object is again D_1 at time T_J (with J different from 1). As a consequence, the distance D_1 appears twice within the set **380** of candidate distances (M_1 is equal to 2). Assume that the set **380** of candidate distances include K different candidate distances. The frequency distribution (also called occurrence) of each candidate distance D_i can be for example defined as $\frac{M_i}{K}$.

The frequency distribution of the candidate distances can be used to estimate the distance between the marine vessel **125** and the marine object (operation **392**).

In some embodiments, the candidate distance which has the highest frequency distribution can be selected as the estimation of the distance between the marine vessel and the marine object. This is not limitative and candidate distances obtained with different frequencies (which do not necessarily correspond only to the highest frequency) can be output.

The method can be repeated for a different period of time $[T_{N+1}; T_M]$.

According to some embodiments, it is possible to use data D_{physical} informative of an expected motion of the marine object, in order to determine the distance to the marine vessel.

Assume that the neural network **160** has been used to estimate, for each image of a plurality of images, one or more candidate distances between the marine vessel and the marine object, thereby obtaining, based on the plurality of images, a set of candidate distances for the given period of time.

Data D_{physical} can be used to determine that at least one candidate distance of the set of candidate distances is not compatible with a (realistic/correct) estimate of a distance between the marine vessel and the marine object.

Indeed, if it is known that the marine object has a speed which cannot exceed a threshold, then the difference between a candidate distance determined for an image at a first time and a candidate distance determined at a second time cannot exceed a given threshold, and therefore this can be used to filter erroneous/unrealistic candidate distances.

Attention is now drawn to **Fig. 4**, which describes a method of training the at least one neural network **160**.

The method includes obtaining (operation **400**) a plurality of images (training set) and labelled data. Each given image of the plurality of images includes a given marine object (or a plurality of image marine objects) acquired by a given imaging device of a given marine vessel. Note that in the training set, the marine objects can be different from one image to another. In some embodiments, the images can be acquired by imaging devices mounted on different marine vessels. In some embodiments, the images can be acquired by imaging devices of different types and/or with a different height and/or with a different orientation, etc.

The labelled data includes, for each given image of the training set, a given label indicative of a distance between the given marine vessel and the given marine object. Embodiments for generating the labelled data are provided hereinafter.

According to some embodiments, the labelled data includes, for each given image, a geometric representation (e.g., bounding box) indicative of the position of the given marine object in the given image. This position in the image can be determined for example by the machine learning module **159**, or using different methods.

The method further includes feeding (operation **410**) the plurality of images and the labelled data to the at least one neural network **160**, for its training.

The neural network **160** tries to predict the distance to the marine object, and a comparison of this prediction with the distance provided in the labelled data can be used to update weights associated with neurons of the layers of the neural network **160**. Methods such as *Backpropagation* can be used to train the neural network **160**.

The weighting and/or threshold values of the neural network **160** can be initially selected prior to training and can be further iteratively adjusted or modified during training to achieve an optimal set of weighting and/or threshold values in a trained neural network. After each iteration, a difference (also called loss function) can

be determined between the actual output produced by the neural network **160** and the target output (e.g., the distance provided in the label) associated with the respective training set of data. The difference can be referred to as an error value. Training can be determined to be complete when a cost or loss function indicative of the error value is less than a predetermined value, or when a limited change in performance between iterations is achieved. If the neural network **160** includes a plurality of NN subnetworks, they can be trained separately, prior to training the entire NN.

According to some embodiments, the labelled data that are fed to the neural network **160** for its training include, for each given image of the training set, data D_{camera} informative of an orientation and/or of a height of the imaging device **120** within a period of time at which the given image has been acquired (operation **430**).

As explained above with reference to **Fig. 2D**, providing the height of the imaging device **120** to the neural network **160** during its training can help the neural network **160** to be adaptive to any height of the imaging device. Robustness of the distance prediction is therefore improved.

Embodiments for determining D_{camera} will be provided hereinafter.

According to some embodiments, the labelled data includes, for each given image of the training set (or for at least some of them), data $D_{\text{environmental}}$ informative of the environment in which the image has been acquired. Note that examples of data for $D_{\text{environmental}}$ have been provided above, as well as non-limitative embodiments to obtain this data, and this description applies hereinafter.

Therefore, $D_{\text{environmental}}$ can be also fed to the neural network **160** as an input for its training.

According to some embodiments, it is possible to feed additional data to the neural network **160** for its training, such as the type of the marine object. The type of the marine object can be provided with the labelled image. Embodiments for determining, automatically, the type of the marine object, are provided hereinafter.

According to some embodiments, the neural network **160** is trained using a set of images and labelled data, each given image of the set of images including a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data includes data **440** (see **Fig. 4**) informative of an orientation of the given marine object as displayed in the given image.

A non-limitative example is provided in **Fig. 5**.

In the left part of **Fig. 5**, the marine vessel **520** is travelling towards the marine vessel on which the imaging device acquiring the image **530** is mounted.

In the right part of **Fig. 5**, the same marine vessel **520** is travelling along a trajectory orthogonal to an optical axis of the imaging device acquiring the image **540**.

As visible from the example of **Fig. 5**, the size and the dimensions of the marine vessel are not the same depending on its orientation in the image. This can impact the distance estimation performed by the neural network **160**.

Therefore, in some embodiments, data **440** informative of the orientation of the marine object in the image is fed to the neural network **160**. This can help improving accuracy of the distance estimation when training the neural network **160**.

In some embodiments, data **440** informative of the orientation of the marine object can be determined using the AIS of the marine object (which provides the position and the course of the marine object) and the position of the marine vessel (which is known using sensors of the marine vessel) on which the imaging device is mounted. Based on these data, it is possible to estimate the trajectory of the marine object relative to the marine vessel, and, in turn, the orientation of the marine object in the images acquired by the imaging device of the marine vessel.

In some embodiments, data **440** can be used also during prediction, that is to say that data **440** can be fed to the trained neural network **160** (in addition to the image of a marine object acquired by the imaging vessel) to improve the estimation of the distance to the marine object by the trained neural network **160**. This is however not mandatory.

In some embodiments, the neural network **160** is trained using images acquired by one or more imaging devices of one or more marine vessels which are not necessarily the same as the marine vessel which is used to acquire images during the prediction phase.

Attention is now drawn to **Fig. 6A**.

Assume that the neural network **160** has been used to determine a distance from the marine vessel **125** to a given marine object. In some embodiments, performance of the neural network in this distance estimation can be assessed (operation **610**). In particular, it can be determined that the estimation of the distance by the neural network **160** does not meet a quality criterion.

Operation **610** can include e.g., comparing the distance output by the neural network to the true distance (the true distance can be provided e.g., using other sensors, such as AIS). If the difference is above a threshold, this indicates that the estimation does not meet the quality criterion. In a non-limitative example, the threshold is around 200m

(this value is not limitative). Note that the threshold can vary depending on the distance to the marine object.

Operation **610** can include checking the level of confidence of the neural network **160** in its estimation. Indeed, in some embodiments, the neural network **160** can provide a level of confidence (or probability) that its output is correct. If the level of confidence is below a threshold, this indicates that the estimation does not meet the quality criterion.

Operation **610** can include analysing the distribution of candidate distances. This distribution should tend to a Gaussian curve (this is not limitative). However, a distribution in which the candidate distances have similar probabilities is indicative of the fact that the neural network **160** did not manage to estimate the correct distance (see a non-limitative example of such distribution **600** as illustrated in **Fig. 6B**). This indicates that the estimation does not meet the quality criterion. In other words, the distribution of candidate distances does not meet a criterion (e.g., does not match a Gaussian curve), and therefore, as explained hereinafter, the neural network **160** should be retrained.

If estimation of the distance by the neural network **160** does not meet the quality criterion, the method of **Fig. 6A** can further include determining (operation **620**) a scenario in which the image has been acquired. Note that the scenario can be also determined based on a plurality of images of one or more marines objects for which the neural network tends to underperform in its distance estimation.

In some embodiments, it can be determined that the image has been acquired under given environmental conditions. This can be determined using e.g. the data $D_{\text{environmental}}$. For example, it can be determined that the distance estimation by the neural network **160** tends to underperform in a rainy day.

In some embodiments, it can be determined that the image which has been acquired is the image of a given type of marine object. For example, it can be determined that the distance estimation by the neural network **160** tends to underperform for fishing vessels.

In some embodiments, it can be determined that the image which has been acquired corresponds to a specific location at sea (e.g., at shore), or specific background in the image (e.g., at shore and not in open sea).

In some embodiments, it can be determined that the image which has been acquired corresponds to a specific height or range of heights of the imaging device.

In some embodiments, it can be determined that the image has been acquired at a given distance or range of distances. For example, it can be determined that the distance estimation by the neural network **160** at a distance above 5 miles tends to underperform.

In some embodiments, it can be determined that the image has been acquired for a specific orientation of the one or more marine objects as displayed in the given images. For example, it can be determined that the distance estimation by the neural network **160** tends to underperform for marine objects which travel towards the marine vessel.

In other words, this indicates that for a given scenario, the deep neural network **160** tends to underperform, and should therefore be retrained specifically for this type of given scenario.

The method of **Fig. 6A** can further include retraining (operation **630**) the neural network with a training set which matches the scenario according to a matching criterion.

For example, if it has been determined that the image has been acquired on a rainy day, a training set including images acquired on a rainy day can be used.

Alternatively, if it has been determined that the image has been acquired at long distance of the marine object (e.g., over 5 miles), then the training set includes images of marine objects located at a distance greater than 5 miles.

In other words, a retraining of the neural network is performed which focuses on the scenario/types of input data in which the neural network tends to underperform.

For example, it has been detected that the neural network **160** tends to underperform in distance estimation for fishing vessels located at shore at a distance over 5 miles (this example is not limitative). A training set of images corresponding to this scenario can be obtained and fed to the neural network **160** for retraining the neural network **160**, thereby enabling the neural network **160** to improve its performance in the scenario in which it tends to underperform.

Note that in some embodiments, it is possible to generate detailed benchmarks for analyzing the performance of the neural network **160**. For each of a plurality of given scenarios, the distance estimation of the neural network **160** is assessed to verify whether it meets the quality criterion. If, for a given scenario, it has been established that the quality criterion, the neural network **160** can be retrained using images which have been acquired under conditions corresponding specifically to this given scenario.

Attention is now drawn to **Fig. 7**, which describes a method of determining data D_{camera} informative of a height and/or orientation of an imaging device. As explained

hereinafter, this method can be used also to generate automatic labelling of images of marine objects (the label including the distance to the marine object).

As shown in **Fig. 7**, the method includes obtaining (operation **700**) first data informative of first marine objects.

The first data is obtained based on images acquired by the imaging device **120** of the marine vessel **125**. In some embodiments, the first data is obtained based on images acquired by a plurality of imaging devices **120** of the marine vessel **125**. The first data includes first position data informative of a position of first marine objects.

Generally, the first position data is expressed in the referential of the imaging device **120**. A PMC is configured to detect, in a given image acquired by the imaging device **120**, marine objects present in the image. As mentioned above, this detection can rely on an image processing algorithm.

Once a given marine object is detected in an image acquired by the imaging device **120**, its position (e.g., pixel position comprising a position along the X axis of the image and a position along the Y axis of the image) in the image can be obtained. Therefore, for each marine object acquired by the imaging device **120**, a position in the image can be obtained. The first position data can include, in some embodiments, the position of each given object of the first marine objects in the image in which the given object has been detected.

According to some embodiments, the imaging device **120** acquires a plurality of images at a plurality of periods of time. As a consequence, it is possible to obtain position over time of the first marine objects.

In particular, the method can include obtaining a set of first position data (see operation **700₁** in **Fig. 2A**). The set of first position data includes, for each object of the first marine objects, position of the object at the plurality of periods of time.

Indeed, since the marine vessel **125** moves over time and/or at least some of the first marine objects move over time, the position of the first marine objects in the images acquired by the imaging device **120** can change over time.

According to some embodiments, in order to generate the set of first position data, it is possible to track the first marine objects in the plurality of images acquired by the imaging device **120**.

A non-limitative example is provided with reference to **Fig. 7B**.

Assume that at time t_1 , an image is acquired by the imaging device **120**. In this image, three marine objects are detected. A first marine object is located at position **730**,

a second marine object is located at position **731**, and a third marine object is located at position **732**.

At time t_2 (different from t_1), another image is acquired by the imaging device **120**. In this image, three marine objects are detected. A first marine object is located at position **733**, a second marine object is located at position **734**, and a third marine object is located at position **735**.

At time t_3 (different from t_2), another image is acquired by the imaging device **120**. In this image, three marine objects are detected. A first marine object is located at position **736**, a second marine object is located at position **737**, and a third marine object is located at position **738**.

A tracking method can be used to track the various marine objects over the different images. The tracking method can be implemented by a PMC. The tracking method can implement e.g., a Kalman filter, or other adapted tracking methods.

In some embodiments, it can appear that a marine object is present in some of the images and disappear in subsequent images. This can be due to the relative motion between the marine object and the marine vessel **125**.

In the example of **Fig. 7B**, the tracking method reveals that the marine object located at position **730** at time t_1 , the marine object located at position **733** at time t_2 and the marine object located at position **736** at time t_3 correspond to the same object at different periods of time. Therefore, the same tracking ID (in this example “(1)”) can be assigned to indicate that the same marine object is present at different positions in the different images.

Similarly, the tracking method reveals that the marine object located at position **731** at time t_1 , the marine object located at position **734** at time t_2 and the marine object located at position **737** at time t_3 correspond to the same marine object at different periods of time. Therefore, the same tracking ID (in this example “(2)”) can be assigned.

Similarly, the tracking method reveals that the marine object located at position **732** at time t_1 , the marine object located at position **735** at time t_2 and the marine object located at position **738** at time t_3 correspond to the same marine object. Therefore, the same tracking ID (in this example “(3)”) can be assigned.

The method includes obtaining **(710)** second data informative of second marine objects.

Although **Fig. 7** depicts a sequence in which the first position data is first obtained and then the second position data, this is not mandatory, and this can be performed in the opposite way, or simultaneously. This is also true for the sequence depicted in **Fig. 7A**.

The second data is obtained based on data acquired by at least one sensor **115** of the marine vessel **125**. Sensor **115** is different from imaging device **120**. In some embodiments, sensor **115** is not an imaging device (e.g., not a camera). Various examples have been provided above for sensor **115** (e.g., a radar, AIS, etc.).

The second data includes second position data informative of a position of second marine objects encountered by the marine vessel **125** during its voyage. As explained hereinafter, according to some embodiments, the method projects position of the targets detected by the various sensors (which can be expressed in different referentials) within a common referential.

In some embodiments, a plurality of sensors **115** is available, which includes sensors **115** of different types (e.g., a first sensor is a radar, a second sensor is AIS, a third sensor is GPS, etc.). In this case, for each sensor, position data of marine objects detected by this sensor is obtained. As explained hereinafter, each sensor can detect different marine objects, but at least a plurality of the marine objects surrounding the marine vessel **125** is detected by different sensors **115**.

At least some of the first marine objects and the second marine objects correspond to the same physical marine objects. For example, the first marine objects include a first given marine vessel, a second given marine vessel, and a buoy. The second marine objects include the first given marine vessel, the second given marine vessel, and an iceberg.

This difference between the first marine objects and the second marine objects can be due to the fact that the imaging device **120** and the other sensors **115** have a different field of view, and/or a different line of sight, and/or different capabilities of detecting objects (e.g., depending on the type of the sensor, its capability to detect objects can depend e.g. on weather conditions, size of the object, type of the object, etc.). In addition, the imaging device **120** and the other sensor(s) **115** can present other differences (for example, the imaging device **120** can be used to classify marine objects, which is not possible for all sensors **115**, such as radar).

Distance between the marine vessel **125** and the marine objects can also impact the detection of the marine objects by the sensors of the marine vessel **125**. For example, a radar is operative to detect marine objects at medium-long range, but has a blind zone at short range, whereas the imaging device **120** better performs at short range than at long

range for detecting marine objects. Therefore, not all marine objects are detected by all sensors of the marine vessel **125**.

In some embodiments, the first marine objects and the second marine objects are the same. This means that all sensors **130** have been able to detect the same marine objects.

The second position data is expressed in a referential which can depend on the sensor **115**.

For example, if sensor **115** is an AIS, absolute position (latitude, longitude in world coordinates) of the marine objects is obtained.

If sensor **115** is a radar, position of the marine object relative to the marine vessel **125** is obtained (expressed e.g., as a range and an angular position relative to the radar and/or marine vessel **125**).

According to some embodiments, the second data can include additional data (in addition to the second position data of the second marine objects).

According to some embodiments, the second data includes identification data of the second marine objects. For example, the AIS provides identification data specific to each object, which enables its identification.

According to some embodiments, the second data includes data informative of the type (e.g., type of marine vessel, etc.) of the marine object (which can be provided by sensor(s) **115** and/or which can be derived from data provided by sensor(s) **115**).

For example, the AIS can provide type of the marine object.

According to some embodiments, sensor **115** acquires data at a plurality of periods of time (e.g., while the marine vessel **125** is in motion). As a consequence, it is possible to obtain position over time of the second marine objects. As explained hereinafter, tracking data of the marine objects can be used to improve matching/association between the first and second marine objects. This is however not mandatory.

In particular, the method can include obtaining a set of second position data (operation **710₁** in **Fig. 7A**). The set of second position data includes, for each given object of the second marine objects, position of the given object at the plurality of periods of time.

In order to track the second marine objects over the different acquisitions, several methods can be used.

In some embodiments, if sensor **115** provides identification data specific to each object, it is possible to track the object over the plurality of periods of time, thereby enabling generating the set of second position data. For example, if sensor **115** is an AIS,

it is possible to track the position of the objects over time, since each object is associated with specific identification data provided by the AIS.

If sensor **115** is a radar, the objects can be tracked over the various radar acquisitions (that is to say, at the plurality of periods of time), using regular radar tracking.

According to some embodiments, the first position data informative of a position of first marine objects (respectively, the set of first position data) corresponds to a position at a first period of time (respectively, at a plurality of first periods of time), and the second data informative of a position of second marine objects (respectively, the set of first position data) corresponds to a position at a second period of time (respectively, at a plurality of second periods of time).

The first period of time (respectively first periods of time) and the second period of time (respectively second periods of time) meet a synchronization criterion. The synchronization criterion ensures that the time difference between the respective first period(s) of time and the respective second period(s) of time is below a threshold. For example, the synchronization criterion can ensure that a time difference between the respective first period(s) of time and the respective second period(s) of time is below 1 sec. This value is however not limitative. In particular, if the respective first period(s) of time and the respective second period(s) of time do not meet the synchronization criterion, it is possible to perform up-sampling of the data provided by the sensors (using e.g., a Kalman filter – this is not limitative). Similarly, if necessary, down-sampling can be performed.

As a consequence, the first period(s) of time and the second period(s) of time are substantially identical.

The method further includes (operation **720**) using the first position data and the second position data to estimate data informative of at least one of a height and an orientation of the imaging device **120**. In some embodiments, both data informative of a height and an orientation of the imaging device is estimated, or only part of this data (e.g., because at least some of this data is already known, using e.g., other sensors and/or external input). Generally, at least one of the height and the orientation of the at least one imaging device is variable over time, since orientation and/or position of the marine vessel evolves over time.

Data informative of an orientation of the imaging device **120** includes at least one of a roll of the imaging device **120**, a pitch of the imaging device **120**, a yaw of the imaging device **120**, etc. This orientation can be expressed similarly as roll/pitch/yaw of a ship (for

example, the roll axis is an imaginary line running horizontally through the length of the ship, through its centre of mass, and parallel to the waterline, the pitch axis is an imaginary line running horizontally across the ship and through its centre of mass, and the yaw axis is an imaginary line running vertically through the ship and through its centre of mass).

Data informative of a height (also called altitude or elevation) of the imaging device **120** can be also estimated. Height of the imaging device **120** can be expressed for example relative to sea level (also called mean sea level – MSL, or relative to still-water level – SWL).

Once one or more parameters of the imaging device **120** have been determined, additional position data (e.g., absolute position of the imaging device) can be determined.

As mentioned above, in some embodiments, position data of the marine objects at a plurality of periods of time is obtained.

According to some embodiments, the method can include using (operation **720**₁ in **Fig. 2A**) the set of first position data (which includes position of the first marine objects at a plurality of periods of time derived from images acquired by the imaging device **120**) and the set of second position data (which includes position of the second marine objects at a plurality of periods of time derived from data acquired by sensor **115**) to estimate data informative of at least one of a position and an orientation of the imaging device **120** over time.

As explained hereinafter, estimating data informative of height and/or orientation of the imaging device **120** can include attempting to match position of the first marine objects and position of the second marine objects (in order to reflect the fact that they correspond to the same marine objects acquired by different sensors), by modifying the value of the height and/or orientation of the imaging device **120** (which is to be estimated). In other words, estimation of the height and/or orientation of the imaging device **120** also enables to match various targets acquired by the image and one or more additional sensors.

According to some embodiments, a filter (e.g., probabilistic filter) can be used which predicts the expected variations in orientation and/or height of the imaging device **120** (depending e.g., on the weather conditions). This is useful to filter out estimation of the height and/or orientation of the imaging device **120** which is not realistic and corresponds to noise.

Fig. 7C illustrates a method in which data informative of at least one of a height and an orientation of the imaging device **120** of the marine vessel **125** is estimated over time. As shown in **Fig. 7C**, the method is iterative over time.

The method includes obtaining (operation **700_i**) first position data informative of a position of first marine objects $\text{FIRSTMOBJ}_{1,i}$ to $\text{FIRSTMOBJ}_{N,i}$ at a first period of time $T_{1,i}$, wherein the first position data is obtained based on images acquired by the imaging device **120** of the marine vessel **125**. Operation **700_i** is similar to operation **200**.

The method includes obtaining (operation **710_i**) second position data informative of a position of second marine objects $\text{SNDMOBJ}_{1,i}$ to $\text{SNDMOBJ}_{M,i}$ at a second period of time $T_{2,i}$, wherein the first period of time $T_{1,i}$ and the second period of time $T_{2,i}$ meet a synchronization criterion (see above a possible definition of this criterion). The second position data is obtained based on data acquired by the at least one sensor **115** of the marine vessel **125**. Operation **210_i** is similar to operation **210**.

At least some of the first marine objects $\text{FIRSTMOBJ}_{1,i}$ to $\text{FIRSTMOBJ}_{N,i}$ are the same as at least some of the second marine objects $\text{SNDMOBJ}_{1,i}$ to $\text{SNDMOBJ}_{M,i}$.

The method includes (operation **720_i**) using the first position data and the second position data to estimate data informative of at least one of a height and an orientation of the imaging device **120** of the marine vessel **125**. Operation **220_i** is similar to operation **220**. As a consequence, data informative of at least one of a height and an orientation of the imaging device **120** is estimated at a given period of time T'_i , which substantially coincides with the first period of time $T_{1,i}$ and the second period of time $T_{2,i}$ (as mentioned, the first period of time $T_{1,i}$ and the second period of time substantially $T_{2,i}$ coincide since they meet a synchronization criterion). In other words, $T'_i \approx T_{1,i} \approx T_{2,i}$.

As shown in **Fig. 2C**, operation **700_i** is repeated at a different first period of time $T_{1,i+1}$ (which occurs after $T_{1,i}$ - i has been incremented by one in the flow chart of **Fig. 2C**). Therefore, at time $T_{1,i+1}$, first position data informative of a position of first marine objects $\text{FIRSTMOBJ}_{1,i+1}$ to $\text{FIRSTMOBJ}_{N,i+1}$ is obtained. It has to be noted that the first marine objects $\text{FIRSTMOBJ}_{1,i+1}$ to $\text{FIRSTMOBJ}_{N,i+1}$ of time T_{i+1} can differ from the first marine objects $\text{FIRSTMOBJ}_{1,i}$ to $\text{FIRSTMOBJ}_{N,i}$ of time T_i . This is however not mandatory, and depends on the scenario (in some cases, there is a partial overlap).

Operation **710_i** is repeated at a different second period of time $T_{2,i+1}$ (which occurs after $T_{2,i}$). Therefore, at time $T_{2,i+1}$, second position data informative of a position of second marine objects $\text{SNDMOBJ}_{1,i+1}$ to $\text{SNDMOBJ}_{M,i+1}$ is obtained. It has to be noted that the second marine objects $\text{SNDMOBJ}_{1,i+1}$ to $\text{SNDMOBJ}_{M,i+1}$ of time T_{i+1} can differ from the second marine objects $\text{SNDMOBJ}_{1,i}$ to $\text{SNDMOBJ}_{M,i}$ of time T_i . This is however not mandatory, and depends on the scenario (in some cases, there is a partial overlap).

$T_{1,i+1}$ and $T_{2,i+1}$ meet a synchronization criterion.

At least some of the first marine objects $\text{FIRSTMOBJ}_{1,i+1}$ to $\text{FIRSTMOBJ}_{N,i+1}$ are the same as at least some of the second marine objects $\text{SNDMOBJ}_{1,i+1}$ to $\text{SNDMOBJ}_{M,i+1}$.

Operation **720_i** is repeated in order to estimate data informative of at least one of a height and an orientation of the at least one imaging device of the marine vessel. As a consequence, data informative of at least one of a height and an orientation of the imaging device **120** is estimated at a given period of time T'_{i+1} , which substantially coincides with the first period of time $T_{1,i+1}$ and the second period of time $T_{2,i+1}$ (as mentioned, the first period of time $T_{1,i+1}$ and the second period of time substantially $T_{2,i+1}$ coincide since they meet a synchronization criterion). In other words, $T'_{i+1} \approx T_{1,i+1} \approx T_{2,i+1}$.

The method therefore enables to estimate at least one of a height and an orientation of the imaging device **120** over time.

According to some embodiments, height and/or orientation of the imaging device **120** is estimated in real time or quasi real time (a small delay can be present due to the time for the sensors of the marine vessel to acquire the data, and the time for processing this data).

Assume that data informative of at least one of a height and an orientation of the imaging device **120** is estimated at a given period of time (corresponding to a given iteration i of the method of **Fig. 7C**). In some embodiments, this data can be used to improve estimation of at least one of a height and an orientation of the imaging device **120** at a subsequent period of time (corresponding to a given iteration $i+1$ of the method of **Fig. 7C**). For example, the estimation obtained at iteration i can be used as a starting point of the algorithm which attempts to estimate the height and/or orientation at iteration $i+1$. In other words, results of a previous iteration can be used to improve estimation at a subsequent iteration.

In some embodiments, and as explained hereinafter, estimation of the height and/or orientation of the imaging device **120** includes determining an association or match between the first marine objects and the second marine objects at a given iteration. The association determined at a given iteration “ i ” of the method can be reused as an input of the method at a subsequent iteration “ $i+1$ ” (or more generally at an iteration “ j ”, with $j > i$), to improve determination of the association at the subsequent iteration. For example, as explained hereinafter, if two given marine objects have been identified as matching at a previous iteration of the method of **Fig. 7C**, a term (reward) can be introduced in a loss function (calculated at a subsequent iteration of the method – see hereinafter embodiments which rely on a loss function) which takes into account this information.

Fig. 7D illustrates an embodiment of a method which can be used to perform operation **720** or operation **720_i** or operation **720_i**.

As shown in **Fig. 7D**, the method includes projecting (**721**) first position data informative of a position of the first marine objects, and second data informative of a position of the second marine objects, into a common referential.

Although **Fig. 7D** depicts a sequence in which the first position data is first projected, and then the second position data, this is not limitative, and this could be performed in the opposite way, or simultaneously.

The common referential can correspond e.g., to a global/absolute referential such as world coordinates (latitude, longitude). This is not limitative and other referentials can be used. For example, a predefined set of coordinates which share the same plane can be used (for example the set of coordinates is expressed relative to the marine vessel's position, which is selected as the origin of the set of coordinates).

As explained above, the first position data is generally expressed in the referential of the image (referential of the imaging device **120**).

In order to convert the first position data into the common referential, an assumption on the data informative of the height and/or orientation of the imaging device **120** can be made.

Based on this assumption, and the known position of the first marine objects in the referential of the image(s) acquired by the imaging device **120**, it is possible to project the first position data from the referential of the image into the common referential.

A method of projecting the first position data into the common referential is described hereinafter with reference to **Fig. 7F**.

In some embodiments, at least some of the position data is already expressed in the common referential.

For example, an AIS may provide position data in world coordinates.

If position data is provided by a radar, it is possible to convert the position data in world coordinates by using the position of the marine vessel **125**. Indeed, since the radar provides relative position (range/bearing), and the position of the marine vessel **125** is known (using e.g., a localization system such as GPS/AIS of the marine vessel **125**), it is possible to project the position data into world coordinates (or into another common referential).

Fig. 7E illustrates a projection of the first position data and the second position data into a common referential **752** (a global/absolute referential, such as an Earth referential).

Projection of the first position data into the common referential **752** depends *inter alia* on the height and orientation of the imaging device **120**.

At this stage, since height and/or orientation of the imaging device **120** is unknown (or known with an error), the first position data is projected randomly, and therefore position of the first marine objects (depicted as triangles) does not match position of the second marine objects (depicted as circles).

Fig. 7F illustrates a method of projecting the first position data from the referential of the image into a common referential (global/absolute referential – independent of the referential of the image).

It has to be noted that this method is not limitative, and is provided as an example only.

Assume that a given marine object **799** (depicted in **Fig. 7J**) has been identified in an image acquired by the imaging device **120**.

For example, a bounding box (see **Fig. 7G**, “*target_bounding_box*”) including the given marine object **799** is obtained. Assume the following notations:

- i. $(left_{upper_x}, left_{upper_y})$ correspond to the coordinates of the left upper point of the bounding box (in the image);
- ii. $(right_{bottom_x}, right_{bottom_y})$ correspond to the coordinates of the right lower point of the bounding box (in the image);
- iii. $cam_{vert_{fov}}, cam_{hor_{fov}}$ correspond respectively to the imaging device vertical field of view and to the imaging device horizontal field of view;
- iv. img_w and img_h correspond to the image resolution (width by height);
- v. cam_{lat}, cam_{long} correspond respectively to the latitude and longitude of the imaging device **120**;
- vi. cam_{height} corresponds to the height of the imaging device **120**, relative to sea level (it is assumed that the marine vessel **125** and the given marine object are located at the same water surface);
- vii. cam_{pitch}, cam_{roll} and cam_{yaw} correspond respectively to the pitch of the imaging device **120**, the roll of the imaging device **120** and the yaw of

the imaging device **120** (it is generally assumed that the imaging device **120** and the marine vessel **125** form a rigid body); and

- viii. $targ_{lat}$ and $targ_{lon}$ correspond respectively to the latitude of the given marine object and the longitude of the given marine object;

Parameters (i) to (vii) are the input of the method, and parameter (viii) is an output of the method.

The method includes converting (operation **790**) the coordinates of the two extremities of the bounding box into a single point, with coordinates $(target_x, target_y)$.

$$target_x = \frac{left_{upper_x} - right_{bottom_x}}{2}$$

$$target_y = \frac{left_{upper_y} - right_{bottom_y}}{2}$$

The method includes converting (**791**) the coordinates $(target_x, target_y)$ of the given marine object into a bearing (noted $global_bearing$) of the given marine object expressed in an absolute referential (e.g., Earth referential), as detailed hereinafter.

$$left_{img_angle} = -\frac{cam_hor_fov}{2}$$

$$right_{img_angle} = \frac{cam_hor_fov}{2}$$

$$onimg_bearing = \frac{\left(target_x (right_{img_angle} - left_{img_angle}) \right)}{img_w} + left_{img_angle}$$

$$global_bearing = (onimg_bearing + cam_yaw + 360) \bmod(360)$$

The method further includes (**792**) determining an artificial horizon line equation in the image (the artificial horizon line corresponds to a reference for which the imaging device **120** has zero roll and zero pitch). **Fig. 7H** illustrates a non-limitative example of an artificial horizon line and some of the parameters which are used to determine its equation.

A normalization function $old_to_new_value(old_value, old_range, new_range)$ is defined, in which old_value is the value that needs to be normalized, old_range corresponds to the current range (old_{min}, old_{max}) , new_range corresponds to the expected value range (new_{min}, new_{max}) and new_value corresponds to the output of the function. The function $old_to_new_value$ can be defined as follows:

$$new_value = \left(\frac{((old_value - old_{min})(new_{max} - new_{min}))}{old_{max} - old_{min}} \right) + new_{min}$$

Operation **792** can include setting cam_{pitch} as the output of $old_to_new_value(cam_{pitch}, (-90, 90), (0, 180))$.

Operation **792** can further include calculating the artificial horizon line location in the image in pixels.

This can include determining $pixel_{pitch}$ as follows:

$$pixel_{pitch} = old_to_new_value(cam_{pitch}, (90 - \frac{cam_{vertfov}}{2}, 90 + \frac{cam_{vertfov}}{2}), (0, img_h)).$$

This can further include updating $pixel_{pitch}$ as follows:

$$pixel_{pitch} = abs(\cos(cam_{roll}))pixel_{pitch}.$$

This can further include defining (x_1, y_1) as follows:

$$(x_1, y_1) = \left(\frac{img_w}{2}, pixel_{pitch} \right)$$

(x_1, y_1) corresponds to a first point of the artificial horizon line (see **Fig. 7H**).

This can further include defining (x_2, y_2) as follows:

$$\begin{aligned} (x_2, y_2) &= \left(\frac{img_w}{2}, 0 \right), \text{ if } cam_{pitch} = 90; \\ (x_2, y_2) &= \left(\frac{img_w}{2}, y_1 \right), \text{ if } cam_{pitch} = 0 \text{ or } 180; \\ (x_2, y_2) &= \left(\frac{img_w}{2}, \frac{(y_1 + img_w \tan(cam_{roll}))}{2} \right), \text{ for other values of } cam_{pitch}. \end{aligned}$$

(x_2, y_2) corresponds to a second point of the artificial horizon line (see **Fig. 7H**).

The equation of the artificial horizon line can be calculated using (x_1, y_1) and (x_2, y_2) .

The method further includes (**793**) determining an angle (noted $angle_to_artificial_horizon$) of the given marine object with respect to the artificial horizon line (see **Fig. 7I**). Operation **793** can include determining a distance (see **Fig. 7I**, $pixel_dist_to_artificial_horizon$) in pixels in the image between the bounding box of the given marine object (see **Fig. 7I**, $target_bounding_box$) and the artificial horizon line (this can be performed by a simple trigonometry calculation). Operation **793** can then include determining $angle_to_artificial_horizon$ using the following computation:

$$\begin{aligned} angle_{per_pixel} &= \frac{cam_{vertfov}}{img_h} \\ angle_to_artificial_horizon &= \\ pixel_dist_to_artificial_horizon * angle_{per_pixel} \end{aligned}$$

The method further includes (794) determining a distance (Euclidean distance, noted $euclidean_{dist}$) between the marine vessel 125 and the given marine object 799, as detailed hereinafter. Operation 794 can include a preliminary step of determining an ortho distance (see Fig. 7J – noted hereinafter $ortho_{dist}$) between the marine vessel 125 and the given marine object 799.

$$ortho_{dist} = \tan(90 - angle_to_artificial_horizon) cam_{height}$$

In some embodiments, $ortho_{dist}$ can be corrected to take into account curvature of the Earth (see e.g. <https://earthcurvature.com>).

Operation 794 can then include performing the computation:

$$euclidean_{dist} = \frac{ortho_{dist}}{\cos(abs(onimg_{bearing}))}$$

The method further includes (795) determining absolute coordinates (latitude, longitude) of the given marine object 799. Operation 795 can include the following computation:

$$\begin{aligned} targ_{lat} &= \arcsin(\sin(cam_{lat}) \cos\left(\frac{d}{R}\right) + \cos(cam_{lat}) \sin\left(\frac{d}{R}\right) \cos(bearing)) \\ targ_{lon} &= targ_{lat} \\ &\quad + atan2\left(\cos\left(\frac{d}{R}\right) \right. \\ &\quad \left. - \sin(cam_{lat}) \sin(targ_{lat}), \sin(b) \sin\left(\frac{d}{R}\right) \cos(cam_{lat})\right) \end{aligned}$$

In this equation, d is equal to $euclidean_{dist}$, R is the Earth's radius, and b is equal to $global_{bearing}$.

The method of Fig. 7D further includes (operation 722) solving an optimization problem. In particular, data D_{camera} informative of a height and/or an orientation of the imaging device 120 is estimated to enable matching of position of at least some of the first marine objects determined using D_{camera} and the first position data, and second position data of at least some of the second marine objects. If D_{camera} is changed, projection of the first marine objects from the referential of the image (first position data) into the common referential 252 is changed (as visible in the equations provided above with reference to Figs. 7F to 7J – see parameters cam_{pitch} , cam_{roll} , cam_{yaw} and cam_{height}).

This matching can be according to a criterion (as explained hereinafter, the criterion can define e.g., a number of iterations of the method and/or a minimal value for a loss function).

As mentioned above, modification of an estimation of the height and/or orientation of the imaging device **120** (“ D_{camera} ”) induces that a projection of the position of the first marine objects from the referential of the image (first position data) into the common referential **752** is modified. Modification of D_{camera} does not affect the projection of the position of the second marine objects acquired by other sensors into the common referential **752**.

Solving the optimization problem can include optimizing the estimation D_{camera} of the height and/or orientation of the imaging device **120** to optimize a matching between the position of the first marine objects (as recalculated using D_{camera} and the first position data) and the position of the second marine objects in the common referential. In particular, it is attempted to match between a position of a first marine object and a position of a second marine object which correspond to the same marine object.

In some embodiments, it is possible to estimate additional parameters of the imaging device **120**, such as the field of view (data $D_{\text{field_of_view}}$, such as $cam_{\text{vert_fov}}$ and $cam_{\text{hor_fov}}$) of the imaging device **120**. Although the field of view of the imaging device is generally known, there can be a distortion which can be estimated.

In this case, solving the optimization problem can also include optimizing the values of the field of view to optimize a matching between the position of the first marine objects (as recalculated using D_{camera} , $D_{\text{field_of_view}}$ and the first position data) and the position of the second marine objects in the common referential.

As visible in **Fig. 7D**, the method is generally iterative (see reference **723**). In other words, solving the optimization problem can include various iterations (e.g. N iterations, with $N > 1$), in which at each iteration D_{camera} (and/or $D_{\text{field_of_view}}$) is refined to optimize a loss function, until a convergence criterion is met. In some embodiments, the convergence criterion can define a number of iterations, a value to be reached for the loss function, etc.

In some embodiments, the convergence criterion depends on the number (e.g., absolute number or ratio) of associations/matching that have been performed between the first marine objects and the second marine objects. Indeed, the higher the number associations/matching between the first marine objects and the second marine objects, the higher the prospects that an optimal solution to the optimization problem has been found (and the better the estimation of the orientation and/or height of the imaging device).

At each iteration, it is attempted to improve the estimation of the height and/or orientation of the imaging device **120**, such that the matching between the position of the

first marine objects and the position of the second marine objects in the common referential is improved.

Iteration of the method can include repeating operations **721** and **722**.

Fig. 7K illustrates a projection of the first position data and the second position data into a common referential **752**, after N iterations of the method.

As shown, the first marine object which had an initial position **750** at the first iteration of the method, has an optimized position **755** (after N iterations of the method) which matches the position **751** of a second marine object.

Similarly, a plurality of respective first marine objects has an optimized position which now matches the position of a plurality of the respective second marine objects.

However, there can be one or more first marine objects which do not match any of the second marine objects. In **Figs. 7E** and **7K**, the first marine object which has position **755** at the first iteration of the method, has an optimized position **760** after N iterations of the method, which does not match any position of the second marine objects. This can be due to the fact that this marine object has been acquired only by the imaging device **120** (and not by other sensors **115**), or to various factors such as noise, etc.

Attention is drawn to **Fig. 7L**.

As explained above (see **Fig. 7A** or **Fig. 7C**), in some embodiments, position of the first marine objects and of the second marine objects is obtained at a plurality of periods of time (set of first position data and set of second position data). This can be used to improve estimation of the height and/or orientation of the imaging device **120**.

Assume that first position data and second position are obtained for time t_i .

The method of **Fig. 2L** includes projecting (operation **724**) first data informative of a position of the first marine objects at time t_i and second data informative of a position of the second marine objects at time t_i into a common referential. Operation **724** is similar to operation **721**.

The method further includes solving (operation **725**) an optimization problem, in which data D_{camera} informative of height and/or orientation of the imaging device **120** (and/or data $D_{\text{field_of_view}}$) is estimated to enable matching of position of the first marine objects at time t_i (as recalculated using D_{camera} and the first position data) and the second position data of the second marine objects at time t_i .

Operation **725** is similar to operation **722**.

For position data of time t_i , the method of **Fig. 7L** can be repeated iteratively (see reference **726**), until a convergence criterion is met. Therefore, an estimation of the height and/or orientation of the imaging device **120** is obtained for time t_i .

The method can be performed again (see reference **727**) at time t_{i+1} (different from time t_i). At time t_{i+1} , position of the first and/or second marine objects may evolve in the common referential.

Estimation of the height and/or orientation of the imaging device **120** of time t_i is not necessarily valid for time t_{i+1} , because height and/or orientation of the imaging device **120** can change during the voyage of the marine vessel **125** (due to various factors mentioned above).

Therefore, the method can include performing operations **724** and operations **725** (these operations can be performed iteratively as depicted in reference **726**), in order to estimate height and/or orientation of the imaging device **120** at time t_{i+1} .

In some embodiments, it is possible to use tracking of the marine objects over time to improve matching between the first marine objects and the second marine objects. In particular, if it has been determined that there is a matching between two given objects (a given object of the first marine objects and a given object of the second marine objects) at different periods of time, there is a high likelihood that the two given objects correspond to the same marine object. Therefore, at subsequent periods of time during which it is attempted to match position of the first marine objects and position of the second marine objects (operation **725**), matching of the two given objects should be assigned with a high weight in the optimization problem. This can be performed by introducing a term (reward) in the loss function which takes into account this information.

A non-limitative example is provided with reference to **Fig. 7M**.

Assume that at time t_1 (after e.g., a plurality of iterations of the method – as depicted in reference **726**), position **770** of a first marine object with tracking ID (1,1) matches a position **771** of a second marine object with tracking ID (2,1), and position **772** of a first marine object with tracking ID (1,2) matches a position **773** of a second marine object with tracking ID (2,2) in a common referential **752**.

Assume that at time t_2 (after e.g., a plurality of iterations of the method), position **774** of a first marine object with tracking ID (1,1) matches a position **771** of a second marine object with tracking ID (2,1), and position **776** of a first marine object with tracking ID (1,2) matches a position **777** of a second marine object with tracking ID (2,2) in the common referential **752**.

At time t_3 , at the first iteration of the method, a first marine object has position **778** and tracking ID (1,1), another first marine object has position **780** and tracking ID (1,2), a second marine object has position **779** and tracking ID (2,1) and another second marine object has position **781** and tracking ID (2,2).

When trying to match the positions of the first marine objects and the second marine objects (operation **725**), it is possible to take into account the tracking IDs (as illustrated in operations **785** and **786** of **Fig. 7N**). Indeed, it has been established at time t_1 and time t_2 that the first marine object with tracking ID (1,1) corresponds to the second marine object with tracking ID (2,1). Similarly, it has been established at time t_1 and time t_2 that the first marine object with tracking ID (1,2) corresponds to the second marine object with tracking ID (2,2).

Therefore, at time t_3 , data informative of the height and/or orientation of the imaging device **120** can be estimated to attempt to match position of the first marine object with tracking ID (1,1) with position of the second marine object with tracking ID (2,1), and to attempt to match position of the first marine object with tracking ID (1,2) with position of the second marine object with tracking ID (2,2) (since there is a high likelihood that these respective positions correspond to the same respective marine object).

Matching of the first and second marine objects relies therefore not only on position, but can rely also on tracking data of the first and second marine objects over time (and/or other parameters, as described hereinafter).

Attention is drawn to **Figs. 3A** and **3B**.

As mentioned above, in some embodiments, the first data informative of the first marine objects and the second data informative of the second marine objects include data informative of a type of the marine objects.

This can be used to improve matching between the first marine objects and the second marine objects.

Indeed, if it is known that two marine objects correspond to the same type of objects, a higher weight should be assigned in the optimization problem to match these two marine objects (at operations **722** or **725**). This can be performed by introducing a term (reward) in the loss function which takes into account this information.

To the contrary, if two marine objects correspond to different types of objects, a low weight should be assigned in the optimization problem to match these two marine objects (at operations **722** or **725**). This can be performed by introducing a term (penalty) in the loss function which takes into account this information.

A non-limitative example is shown in **Fig. 8B**.

Assume that a first marine object has a position **805** in the common referential **820**. The first data includes type of objects and indicates that the first marine object is a marine vessel.

Assume that a second marine object has a position **815** in the common referential **820**. The second data indicates that this second marine object is a marine vessel.

Assume that another second marine object has a position **810** in the common referential **820**. The second data indicates that this second marine object is a buoy.

Although position **805** of the first marine object is closer to position **810** of a second marine object than to position **315** of another second marine object, the method should estimate data informative of height and/or orientation of the imaging device **120** to improve matching between position **805** of the first marine object and position **815** of a second marine object, since these two marine objects both correspond to a marine vessel (whereas the second marine object with position **810** corresponds to a buoy, which is a different marine object).

This is shown in operations **850** and **860** of **Fig. 3A** which illustrates using data informative of a type of the first marine objects and a type of the second marine objects, to improve matching between position of the first marine objects and position of the second marine objects.

More generally, the method can use various parameters or additional input which can assist in improving the matching (or association) between the first marine objects and the second marine objects.

Attention is now drawn to **Fig. 9A**, which depicts a particular embodiment of the method of **Fig. 7**.

The method includes obtaining (operation **900**) first data including first position data informative of a position of first marine objects derived from images acquired by the imaging device **120**. Operation **900** is similar to operation **700**.

The method includes obtaining (operation **910**) second data including second position data informative of a position of second marine objects provided by another sensor **115**. Operation **910** is similar to operation **710**. This other sensor is different from the imaging device **120** and is generally a sensor which is not a camera.

As mentioned above, at least some of the first marine objects and the second marine objects correspond to the same marine objects.

The method further includes determining (operation **920**) a current state for data informative of height and/or orientation of the imaging device **120**.

At the first iteration of the method, the exact height and/or orientation of the imaging device **120** is unknown. Therefore, operation **920** can include generating a random value for the height and/or orientation of the imaging device **120**.

In some embodiments, a first estimation of the height and/or orientation of the imaging device **120** can be available. This first estimation can be provided e.g., by an operator and/or a manufacturer who can have first knowledge on the height and/or orientation of the imaging device **120** (e.g., due to the fact that they installed the imaging device **120** on the marine vessel **125**). However, due to various factors mentioned above, this first estimation is no longer exact during voyage of the marine vessel **125**, and therefore parameters of the imaging device **120** need to be estimated.

In some embodiments, a first estimation of the height and/or orientation of the imaging device **120** can be provided by an operator located on the marine vessel **125**, who measures a first value of the height and/or orientation of the imaging device **120**.

Once a current state is available for the height and/or orientation of the imaging device **120**, first position data of the first marine objects can be projected (operation **930**) into a common referential (e.g., Earth referential – this is however not limitative). An example of this projection is provided in **Fig. 7F**.

Similarly, the second position data can be projected into the common referential, as already explained above.

The method further includes (operation **940**) determining data informative of at least one of a height and an orientation of the imaging device to optimize a matching between position of at least some of the first marine objects and position of at least some of the second marine objects. Examples of an optimization algorithm that can be used include e.g., MSE (Mean Square error), gradient descent, MAE (mean average error), min L2 distance (Euclidean distance), etc. These examples are not limitative.

As mentioned above, operation **940** can include using various additional data to improve matching between the first marine objects and the second marine objects, such as type of marine object, tracking data of marine objects, etc.

A loss function can be calculated to reflect the optimization problem. If the loss function does not meet a convergence criterion (e.g., because its value is above a threshold), the method can be repeated, by repeating operation **940**, in which it is

attempted to improve estimation of the height and/or orientation of the imaging device **120**, in order to improve a match between the loss function and the convergence criterion.

When the loss function of the optimization algorithm meets a convergence criterion (e.g., its value is below a threshold and/or a sufficient number of iterations has been performed), the current state (current estimation) of the height and/or orientation of the imaging device **120** can be output (operation **950**). Similarly, the matching between the first marine objects and the second marine objects can be also output, for further usage, as explained hereinafter, such as automatic labelling of the images of a training set (for example, two marine objects acquired by different sensors can be considered as matching when their position in the common referential, as determined using the estimated height/orientation of the imaging device, is substantially similar, or their distance is below a threshold).

According to some embodiments, the method of **Fig. 9A** includes obtaining first data including first position data informative of a position of first marine objects derived from images acquired by an imaging device **120**, second data including second position data informative of a position of second marine objects provided by a first sensor (see reference **115**) and third data including third position data informative of a position of third marine objects provided by a second sensor (see reference **115**). The first sensor and the second sensor are not imaging devices, and the first sensor can be of a different type than the second sensor. At least some of the first marine objects, the second marine objects and the third marine objects correspond to the same marine objects acquired by different sensors. In this example, the method of **Fig. 9A** can be performed similarly by projecting positions of all marine objects within a common referential (similar to operation **930**) and attempting to determine height and/or orientation of the imaging device **120** which optimize a match between the respective positions of the first, second and third marine objects in the common referential. For example, the height and/or orientation of the imaging device is modified to force the projected position of each of the first marine objects to match, as much as possible, the position of at least one of the second and third marine objects.

It may occur that for a given marine object, it is detected only e.g., by the imaging device and the first sensor, and for another marine object, it is detected only by the first and the second sensors, or only by the imaging device and the second sensor.

As explained hereinafter, once the height and/or orientation of the imaging device **120** is estimated, this data can be used for different marine applications.

According to some embodiments, and as shown in **Fig. 9A**, assume that a matching between a given marine object of the first marine objects and a given marine object of the second marine objects has been found (as mentioned above, in some embodiments, this matching can be obtained after several iterations of the optimization method).

In other words, this indicates that this given marine object has been identified as the same marine object acquired both by the imaging device **120** and another sensor **115**. Therefore, if the other sensor **115** provides second position data informative of the given marine object (e.g. expressed in a global/ absolute referential, such as a world referential - for example, sensor **115** is an AIS), it is possible to determine (operation **960**) position of the given marine object acquired by the imaging device **120** using the second position data, and in turn, a distance between the marine vessel **125** to the given marine object.

Attention is now drawn to **Fig. 9B**, which depicts a variant of the method of **Fig. 9A**.

The method includes obtaining (operation **900**) first data including first position data informative of a position of first marine objects derived from images acquired by an imaging device **120**. Operation **400** is similar to operation **200**.

The method includes obtaining (operation **910**) second data including second position data informative of a position of second marine objects provided by a first sensor (see reference **115**). Operation **910** is similar to operation **710**. This first sensor is different from the imaging device **120** and is generally a sensor which is not a camera.

The method includes obtaining (operation **915**) third data including third position data informative of a position of third marine objects provided by a second sensor (see reference **115**).

The second sensor is different from the first sensor and from the imaging device **120**. According to some embodiments, the second sensor is not a camera.

According to some embodiments, the second sensor is of a different type than the first sensor (e.g., the first sensor is an AIS and the second sensor is a radar or a LIDAR – this is not limitative).

The method can include an intermediate operation **916**, in which at least some of the second marine objects and at least some of the third marine objects are merged, to obtain an aggregated (unified) set of marine objects. This operation is however not limitative.

Each marine object of the aggregated set of marine objects is assigned with position data, which can correspond e.g., to the second position data and/or to the third position data.

Operation **916** can be performed by merging marine objects for which a distance between their positions (in a common referential) is below a threshold, and/or is minimal.

Operation **916** can include solving an optimization problem, in which it is attempted to find pairs of marine objects (each pair including a marine object of the second marine objects and a marine object of the third marine objects), such that the distance between marine objects of each pair is minimized. Optimization algorithms mentioned above can be used.

For example, assume that the first sensor is an AIS and the second sensor is a radar. An AIS provides latitude/longitude of the second marine objects, and it is possible to use the relative range/bearing measurements of the radar and position of the marine vessel **125** to determine latitude/longitude of the third marine objects. Therefore, it is possible to merge the second marine objects and the third marine objects into an aggregated set of marine objects.

Although the method of **Fig. 9A** is depicted with two sensors (in addition to the imaging device **120**), this is not limitative, and any adapted additional sensors (which provide information on position of marine objects surrounding the marine vessel) can be used.

The method further includes, similarly to **Fig. 9A**, determining (operation **920**) the current state for data informative of height and/or orientation of the imaging device **120**.

With the current state for data informative of height and/or orientation of the imaging device, the method includes projecting (operation **930**) first position data into a common referential (e.g., an absolute referential, such as an Earth referential).

Regarding the position data of the aggregated set of marine objects, in some embodiments, this position data is already expressed in the common referential. Indeed, if at least one given sensor (among the first sensor and the second sensor) provides position data in the common referential, then after merging of the second and third marine objects into an aggregated set of marine objects (see operation **916**), it is possible to assign, to each object of the aggregated set of marine objects, position data in the common referential, as provided by the given sensor.

The method further includes determining (operation **939**) data D_{camera} informative of at least one of a height and/or an orientation of the imaging device **120** to optimize a

matching between position of at least some of the first marine objects determined using D_{camera} and the first position data and position of at least some of the marine objects of the aggregated set of marine objects. Operation **939** is similar to operation **940** but differs in that operation **939** includes matching between the first marine objects and the aggregated set of marine objects (obtained using at least two sensors). In some embodiments, operation **939** can include determining $D_{\text{field_of_view}}$.

The method can be iterated (e.g., operation **939** can be repeated to fine tune the estimation of D_{camera}) until a convergence criterion is met and there is a match between the loss function and the convergence criterion.

Once the convergence criterion is met, an estimation of the height and/or orientation of the imaging device **120** can be output (see operation **950**).

As explained hereinafter, once the height and/or orientation of the imaging device **120** is estimated, this data can be used for different marine applications.

Attention is now drawn to **Fig. 10**.

The method includes obtaining (operation **1000**) first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device **120** of a given marine vessel **125**. Operation **1000** is similar to operations **700** and **900** already described above, and is not described again.

The method includes obtaining (operation **1010**) second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel **125**, wherein the at least one sensor is different from the given imaging device **120**, wherein at least some of the first marine objects are the same as at least some of the second marine objects. Operation **1010** is similar to operations **710** and **910** already described above, and is not described again.

As explained in the various embodiments above, a matching can be performed between position of the first marine objects (acquired by the imaging device **120**) and position of the second (or even third, or more) marine objects (acquired by other sensors **115**).

Various methods have been described above to perform this matching (as mentioned above, these methods can also involve determination of data D_{camera} informative of the height and/or orientation of the imaging device **120** which has acquired the image).

Therefore, the method can include determining (operation **1015**) that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor. As mentioned above, this matching between the first and second marine objects can be performed for a plurality of marine objects.

Once this matching has been performed, it is known that a marine object of the first marine objects and a marine object of the second marine objects correspond to the same given marine object, acquired both by the imaging device **120** and the sensor(s) **115** (since their positions are substantially identical, or with a difference below a threshold). In other words, an association between the first marine objects and the second marine objects has been performed.

In order to augment knowledge of the given marine object, it is possible to use this association and the various parameters provided by the different sensors.

In particular, it is possible to determine a parameter of the given marine object, using data provided by the other sensor **115** which has detected this given marine object (since it is known that the respective acquisitions by the imaging device and the at least one sensor **115** correspond to the same physical object).

According to some embodiments, the at least one sensor **115** (e.g., AIS) can provide information on the position of the marine object. Therefore, it is possible to determine the distance to the given marine object in the image (operation **1020**).

As a consequence, it is possible to generate automatically a labelled image, which comprises the image of the marine object and a label indicative of the distance to the marine object (operation **1030**).

More generally, it is possible to generate, automatically, a set of labelled images, which comprises the image of a marine object and a label indicative of the distance to the marine object.

In some embodiments, the automatic labelling can include associating the marine object of the image with other parameters, such as the type of the marine object (or other/additional parameters, such as state of the sea, distance of the marine object, etc.). An automatic labelling (sensor labelling) of marine objects is therefore achieved. The labelled images can be used e.g., for supervised training of the neural network **160** configured to determine the distance of marine objects in images. A training with a higher granularity is therefore achieved.

For example, the AIS provides a type (e.g., “cargo”) of a given marine object. However, this information can be corrupted, since it is provided by the marine object itself. The imaging device can be used to determine the true type of the given marine object (using e.g., a neural network, which detects the type of the object based on the image).

A set of augmented data/parameters can be determined for each marine object.

As a consequence, a database of images of marine objects (with corresponding augmented data/parameters) can be created, which can be used to train the neural network **160**. In particular, for each image, labelled data including distance of the marine object, type of the marine object, etc. can be provided for the training of the neural network **160**.

Embodiments of the presently disclosed subject matter are not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement the teachings of the presently disclosed subject matter as described herein.

The invention contemplates a computer program being readable by a computer for executing one or more methods of the invention. The invention further contemplates a machine-readable memory tangibly embodying a program of instructions executable by the machine for executing one or more methods of the invention.

It is to be noted that the various features described in the various embodiments may be combined according to all possible technical combinations.

It is to be understood that the invention is not limited in its application to the details set forth in the description contained herein or illustrated in the drawings. The invention is capable of other embodiments and of being practiced and carried out in various ways. Hence, it is to be understood that the phraseology and terminology employed herein are for the purpose of description and should not be regarded as limiting. As such, those skilled in the art will appreciate that the conception upon which this disclosure is based may readily be utilized as a basis for designing other structures, methods, and systems for carrying out the several purposes of the presently disclosed subject matter.

Those skilled in the art will readily appreciate that various modifications and changes can be applied to the embodiments of the invention as hereinbefore described without departing from its scope, defined in and by the appended claims.

CLAIMS

1. A system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to implement at least one neural network, wherein the PMC is configured to:
 - obtain at least one image of a marine object, acquired by an imaging device of a marine vessel,
 - feed the at least one image to the at least one neural network, and
 - use the at least one neural network to estimate a distance between the marine vessel and the marine object.
2. The system of claim 1, configured to:
 - obtain at least one image of a marine object, acquired by an imaging device of a marine vessel,
 - obtain data D_{height} informative of a height of the imaging device at a period of time at which the image has been acquired,
 - feed the at least one image and the data D_{height} to the at least one neural network, and
 - use the at least one neural network to estimate a distance between the marine vessel and the marine object.
3. The system of claim 1 or of claim 2, configured to use the at least one neural network to determine, using said at least one image, a plurality of different candidate distances between the marine vessel and the marine object.
4. The system of any one of claims 1 to 3, configured to:
 - obtain a plurality of images of a marine object, acquired by the imaging device of the marine vessel at different instants of time of a given period of time,
 - feed each image of the plurality of images to the at least one neural network,
 - use the at least one neural network to estimate, for each image of the plurality of images, one or more candidate distances between the marine vessel and the marine object, thereby obtaining, based on the plurality of images, a set of candidate distances for the given period of time, and

use the set of candidate distances to estimate a distance between the marine vessel and the marine object within the given period of time.

5. The system of claim 4, configured to:

determine data $D_{\text{distribution}}$ informative of a frequency distribution of the candidate distances within the set of candidate distances, and
use the frequency distribution to estimate a distance between the marine vessel and the marine object.

6. The system of any one of claims 1 to 5, configured to:

obtain data D_{physical} informative of an expected motion of the marine object,
and
use data D_{physical} to estimate a distance between the marine vessel and the marine object.

7. The system of claim 6, configured to:

obtain a plurality of images of a marine object, acquired by the imaging device of the marine vessel at different instants of time of a given period of time,
feed each image of the plurality of images to the at least one neural network,
use the at least one neural network to estimate, for each image of the plurality of images, one or more candidate distances between the marine vessel and the marine object, thereby obtaining, based on the plurality of images, a set of candidate distances for the given period of time, and
use data D_{physical} to determine whether at least one candidate distance of the set of candidate distances is not acceptable as an estimate of a distance between the marine vessel and the marine object.

8. The system of any of claims 1 to 7, configured to:

obtain at least one image of a marine object, acquired by an imaging device of a marine vessel,
feed the at least one image to the at least one neural network,

use the at least one neural network to determine a distribution including a plurality of candidate distances, each candidate distance being associated with a probability,

upon detection that the distribution does not meet a criterion, generate data which indicates that the at least one neural network has to be retrained.

9. The system of any one of claims 1 to 8, configured to determine that a distance estimation performed by the at least one neural network does not meet a quality criterion for one or more given images of one or more marine objects acquired by the imaging device which correspond to a same given scenario.
10. The system of claim 9, configured to retrain the at least one neural network with a training set of images that match the given scenario.
11. The system of claim 9 or of claim 10, configured to identify the given scenario using data associated with the given images, the data including at least one of (i) or (ii) or (iii) or (iv) or (v):
 - (i) a type of the one or more marine objects;
 - (ii) data informative of an environment in which the given images have been acquired;
 - (iii) a range of distances in which at which the or more marine objects are located;
 - (iv) data informative of an orientation of the one or more marine objects as displayed in the given images;
 - (v) a range of heights of the imaging device, for which the given images have been acquired.
12. The system of any one of claims 1 to 11, configured to:
 - obtain at least one image of a marine object, acquired by the imaging device of the marine vessel,
 - obtain data $D_{\text{environmental}}$ informative of an environment in which the image has been acquired,
 - feed the at least one image and data $D_{\text{environmental}}$ to the at least one neural network, and

use the at least one neural network to estimate a distance between the marine vessel and the marine object.

13. The system of any one of claims 1 to 12, configured to provide the distance to a controller of the marine vessel, wherein the controller is operative to control a trajectory of the marine vessel using the distance.

14. The system of any one of claims 1 to 13, configured to:

obtain one or more images of a marine object,

feed the one or more images to the at least one neural network, and

use the at least one neural network to estimate a distance between the marine vessel and the marine object, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel.

15. The system of any one of claims 1 to 14, configured to estimate, by the at least one neural network, a distance between the marine vessel and the marine object using an image of the marine object acquired by the imaging device of the marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device.

16. The system of any one of claims 1 to 15, wherein the at least one neural network has been trained using a set of images and labelled data, each given image of the set of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data comprises, for each given image:

an estimate of a distance between the given marine vessel and the given marine object, and

an estimate of a height of the imaging device at a period of time at which the given image has been acquired.

17. The system of any one of claims 1 to 16, configured to:

obtain at least one image of a marine object, acquired by the imaging device of the marine vessel,

obtain data $D_{\text{orientation}}$ informative of an orientation of the imaging device at a period of time at which the image has been acquired,

feed the at least one image and the data $D_{\text{orientation}}$ to the at least one neural network, and

use the at least one neural network to estimate a distance between the marine vessel and the marine object.

18. The system of any one of claims 1 to 17, wherein the neural network has been trained using a set of images and labelled data, each given image of the set of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data comprises, for each given image, an estimate of a distance between the given marine vessel and the given marine object, wherein the labelled data further comprises, for at least one given image, data informative of an orientation of the given marine object as displayed in the given image.

19. A system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to implement at least one neural network, wherein the PMC is configured to:

obtain a plurality of images, each given image of the plurality of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein each given image is associated with a given label indicative of a distance between the given marine vessel and the given marine object,

feed each given image of the plurality of images together with the given label to the at least one neural network to train the at least one neural network,

wherein the at least one neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of the marine vessel.

20. The system of claim 19, configured to, for each given image of the plurality of images, obtain data D_{height} informative of a height of the given imaging device at

a period of time at which the given image has been acquired, and feed the given image and the data D_{height} to the at least one neural network for its training.

21. The system of claim 19 or of claim 20, configured to, for a given image of the plurality of images, obtain the given label indicative of a distance between the given marine vessel and the given marine object using data provided by at least one of:

- (i) a sensor of the given marine vessel different from the imaging device,
- or
- (ii) a sensor of the given marine object.

22. The system of any one of claims 19 to 21, configured to:

obtain first position data informative of a position of first marine objects, wherein the first position data is obtained based on the given image acquired by the given imaging device of the given marine vessel,

obtain second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects,

determine that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor, and

determine the given label indicative of the given distance between the given marine vessel and the given marine object using data provided by the at least one sensor.

23. The system of any one of claims 19 to 22, configured to, for a given image of the plurality of images:

- (i) obtain data $D_{\text{environmental}}$ informative of an environment in which the given image has been acquired, and feed the given image and the data $D_{\text{environmental}}$ to the neural network for its training, or

- (ii) obtain data $D_{\text{orientation}}$ data informative of an orientation of the given marine object as displayed in the given image, and feed the given image and the data $D_{\text{orientation}}$ to the at least one neural network for its training.
24. The system of any one of claims 19 to 23, configured, for a given scenario in which a given image of a given marine object is acquired by the imaging device, to determine that an estimation of the distance by the neural network does not meet a quality criterion, and retrain the neural network with a training set of images matching the given scenario.
25. The system of any one of claims 19 to 24, wherein at least one of (i) or (ii) is met:
- (i) the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of a marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device, or
 - (ii) the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using one or more images of a marine object acquired by an imaging device of a marine vessel, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel.
26. A system comprising a processor and memory circuitry (PMC), wherein the PMC is operative to:
- obtain first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device of a given marine vessel,
 - obtain second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and

determine that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor,

determine a given distance between the given marine vessel and the given marine object using data provided by the at least one sensor, and

generate a labelled image, wherein the labelled image comprises the given image and a label comprising said given distance.

27. The system of claim 26, configured to determine data D_{camera} informative of at least one of a height and an orientation of the imaging device at a period of time at which the given image has been acquired by the imaging device, which optimize a matching between:

position of at least some of the first marine objects determined using D_{camera} and the first position data, and

second position data of at least some of the second marine objects, according to a criterion.

28. The system of claim 26 or of claim 27, configured to determine a type of the given marine vessel using data provided by the at least one sensor, and associate the type with the labelled image.

29. The system of any one of claims 26 to 28 wherein at least one of (i), (ii) and (iii) is met:

(i) the at least one sensor is not an imaging device;

(ii) the at least one sensor includes at least one of a radar and an automatic identification system (AIS);

(iii) the at least one sensor includes a first sensor and a second sensor, wherein the second sensor is of a different type than the first sensor, and wherein the first sensor and the second sensor are not imaging devices.

30. A method comprising, by a processor and memory circuitry (PMC) implementing at least one neural network,

obtaining at least one image of a marine object, acquired by an imaging device of a marine vessel,

feeding the at least one image to the at least one neural network, and
using the at least one neural network to estimate a distance between the
marine vessel and the marine object.

31. The method of claim 30, comprising:

obtaining at least one image of a marine object, acquired by an imaging
device of a marine vessel,
obtaining data D_{height} informative of a height of the imaging device at a
period of time at which the image has been acquired,
feeding the at least one image and the data D_{height} to the at least one neural
network, and
using the at least one neural network to estimate a distance between the
marine vessel and the marine object.

32. The method of claim 30 or of claim 31, comprising:

obtaining a plurality of images of a marine object, acquired by the imaging
device of the marine vessel at different instants of time of a given period of time,
feeding each image of the plurality of images to the at least one neural
network,
using the at least one neural network to estimate, for each image of the
plurality of images, one or more candidate distances between the marine vessel
and the marine object, thereby obtaining, based on the plurality of images, a set of
candidate distances for the given period of time, and
using the set of candidate distances to estimate a distance between the
marine vessel and the marine object within the given period of time.

33. The method of claim 32, comprising:

determining data $D_{\text{distribution}}$ informative of a frequency distribution of the
candidate distances within the set of candidate distances, and
using the frequency distribution to estimate a distance between the marine
vessel and the marine object.

34. The method of any of claims 30 to 33, comprising determining that a distance
estimation performed by the at least one neural network does not meet a quality

criterion for one or more given images of one or more marine objects acquired by the imaging device which correspond to a same given scenario.

35. The method of claim 34, comprising retraining the at least one neural network with a training set of images that match the given scenario.
36. The method of claim 35, comprising identifying the given scenario using data associated with the given images, the data including at least one of (i) or (ii) or (iii) or (iv) or (v):
- (i) a type of the one or more marine objects;
 - (ii) data informative of an environment in which the given images have been acquired;
 - (iii) a range of distances in which at which the or more marine objects are located;
 - (iv) data informative of an orientation of the one or more marine objects as displayed in the given images;
 - (v) a range of heights of the imaging device, for which the given images have been acquired.
37. The method of any one of claims 30 to 36, comprising obtaining at least one image of a marine object, acquired by an imaging device of a marine vessel, the method further comprising at least one of (i) or (ii):
- (i) obtaining data $D_{\text{environmental}}$ informative of an environment in which the image has been acquired, feeding the image and data $D_{\text{environmental}}$ to the at least one neural network, and using the at least one neural network to estimate a distance between the marine vessel and the marine object, or
 - (ii) obtaining data D_{physical} informative of an expected motion of the marine object and using data D_{physical} to estimate a distance between the marine vessel and the marine object.
38. The method of any one of claims 30 to 37, comprising at least one of (i) or (ii):
- (i) estimating, by the neural network, a distance between the marine vessel and the marine object using an image of the marine object acquired by the imaging device of the marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device, or

(ii) obtaining one or more images of a marine object, feeding the one or more images to the at least one neural network, and using the at least one neural network to estimate a distance between the marine vessel and the marine object, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel.

39. The method of any one of claims 30 to 38, wherein the at least one neural network has been trained using a set of images and labelled data, each given image of the set of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein the labelled data comprises, for each given image:

an estimate of a distance between the given marine vessel and the given marine object, and

at least one of (i) or (ii):

(i) an estimate of a height of the imaging device at a period of time at which the image has been acquired, or

(ii) data informative of an orientation of the given marine object as displayed in the given image.

40. A method comprising, by a processor and memory circuitry (PMC) implementing at least one neural network:

obtaining a plurality of images, each given image of the plurality of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein each given image is associated with a given label indicative of a distance between the given marine vessel and the given marine object,

feeding each given image of the plurality of images together with the given label to the neural network to train the at least one neural network,

wherein the at least one neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of the marine vessel.

41. The method of claim 40, comprising, for each given image of the plurality of images, obtaining data D_{height} informative of a height of the given imaging device

at a period of time at which the given image has been acquired, and feeding the given image and the data D_{height} to the at least one neural network for its training.

42. The method of claim 40 or of claim 41, comprising, for a given image of the plurality of images, obtaining the given label indicative of a distance between the given marine vessel and the given marine object using data provided by at least one of:

- (i) a sensor of the given marine vessel different from the imaging device,
or
- (ii) a sensor of the given marine object.

43. The method of any one of claims 40 to 42, comprising:

obtaining first position data informative of a position of first marine objects, wherein the first position data is obtained based on the given image acquired by the given imaging device of the given marine vessel,

obtaining second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and

determining that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor, and

determining the given label indicative of the given distance between the given marine vessel and the given marine object using data provided by the at least one sensor.

44. The method of any one of claims 40 to 43, comprising, for a given image of the plurality of images, at least one of:

- (i) obtaining data $D_{\text{environmental}}$ informative of an environment in which the given image has been acquired, and feeding the given image and the data $D_{\text{environmental}}$ to the at least one neural network for its training, or

- (ii) obtaining data $D_{\text{orientation}}$ data informative of an orientation of the given marine object as displayed in the given image, and feed the given image and the data $D_{\text{orientation}}$ to the at least one neural network for its training.
45. The method of any one of claims 40 to 44, comprising, for a given scenario in which a given image of a given marine object is acquired by the imaging device, determining that an estimation of the distance by the neural network does not meet a quality criterion and retraining the neural network with a training set of images matching the given scenario.
46. The method of any one of claims 40 to 45, wherein at least one of (i) and (ii) is met:
- (i) the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of a marine vessel, without using data informative of the marine object acquired by a sensor different from the imaging device, or
 - (ii) the neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using one or more images of a marine object acquired by an imaging device of a marine vessel, wherein all of the one or more images of the marine object used by the neural network to estimate the distance between the marine vessel and the marine object have been acquired by a same single imaging device of the marine vessel.
47. A method comprising, by a processor and memory circuitry (PMC):
- obtaining first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device of a given marine vessel,
 - obtaining second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and

determining that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor,

determining a given distance between the given marine vessel and the given marine object using data provided by the at least one sensor, and

generating a labelled image, wherein the labelled image comprises the given image and a label comprising said given distance.

48. A non-transitory storage device readable by a processor, tangibly embodying a program of instructions executable by the processor to perform operations comprising:

obtaining at least one image of a marine object, acquired by an imaging device of a marine vessel,

feeding the at least one image to at least one neural network, and

using the at least one neural network to estimate a distance between the marine vessel and the marine object.

49. A non-transitory storage device readable by a processor, tangibly embodying a program of instructions executable by the processor to perform operations comprising:

obtaining a plurality of images, each given image of the plurality of images comprising a given marine object acquired by a given imaging device of a given marine vessel, wherein each given image is associated with a given label indicative of a distance between the given marine vessel and the given marine object,

feeding each given image of the plurality of images together with the given label to the neural network to train the at least one neural network,

wherein the at least one neural network is usable, after said training, to estimate a distance between a marine vessel and a marine object using an image of the marine object acquired by an imaging device of the marine vessel.

50. A non-transitory storage device readable by a processor, tangibly embodying a program of instructions executable by the processor to perform operations comprising:

obtaining first position data informative of a position of first marine objects, wherein the first position data is obtained based on a given image acquired by a given imaging device of a given marine vessel,

obtaining second position data informative of a position of second marine objects, wherein the second position data is obtained based on data acquired by at least one sensor of the given marine vessel, wherein the at least one sensor is different from the given imaging device, wherein at least some of the first marine objects are the same as at least some of the second marine objects, and

determining that a marine object of the first marine objects and a marine object of the second marine objects correspond to a same given marine object acquired respectively by the given imaging device and the at least one sensor,

determining a given distance between the given marine vessel and the given marine object using data provided by the at least one sensor, and

generating a labelled image, wherein the labelled image comprises the given image and a label comprising said given distance.