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Automating Draft Surveys using Artificial Intelligence

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Abstract
In the modern world, ports are ever looking for a competitive edge over their peers. As processes are continuously improved and refined, efficiency and safety gains are often sought. One area of operations that has seen relatively little modernisation is that of draft surveying, which has followed the same basic principles for hundreds of years, involving trained surveyors manually inspecting the draft marks around the hull of a vessel.

An important part of any transfer of cargo to or from a vessel, particularly solid bulk cargoes, a draft survey is the process in which the weight of cargo on a vessel is determined. Once the draft is known, Archimedes' principle can be used to determine displacement of a vessel and, after making appropriate deductions, the weight of cargo. By performing a draft survey both before and after any loading operations the amount of cargo transferred can be calculated. However, performing a draft survey generally requires cargo transfer operations to be paused for a non-trivial amount of time and may place the surveyors in potentially hazardous situations near mooring lines or underneath overhead objects.

The fields of computer vision and machine learning have made significant improvements in the past years, allowing for novel solutions to problems such as this, requiring human observation and judgement. This paper introduces the Optical Draft Intelligence Network (ODIN) technology (patent pending), which uses wharf mounted CCTV and LiDAR devices, powered by artificial intelligence, to monitor vessel draft in real time, throughout the entirety of stay at berth, as well as providing additional information such as drift detection, list, and trim. This technology can be used by surveyors to instantly obtain the draft from any internet enabled device, reducing both cargo transfer delays and potential safety issues.

Keywords: draft survey, draft, list, artificial intelligence, port operations.

1. Introduction

1.1 Draft Surveying

An essential component in many calculations related to a vessel, the draft of a ship is the vertical distance from the waterline to the keel. Under keel clearance (the distance between the keel and the sea floor) and air draft (the distance from the waterline to the highest point on the vessel) are perhaps the most obvious of these, with ports having minimum requirements in place when needed to ensure a vessel can transit safely. However, the main economic use case of vessel draft is in calculating vessel displacement, which when transporting bulk cargoes is often used as a method to determine the amount of product transferred to or from a vessel (United Nations, 1992). An accurate reading of the draft is required as errors may result in significant over or under representation of the amount of product on a vessel.

Traditionally, the draft has always been determined by having a trained surveyor encircle the vessel to read each set of draft marks. Vessels will generally have six sets of draft marks, located at mid ship and at the forward and aft perpendiculars, on both the port and starboard side. If not physically at these locations, corrections are made to the observed values. Depending on the sea state, each reading may take several minutes, with the entire process generally taking around 30 to 60 minutes to complete.

Once the draft marks have been read, there are several steps to calculate the displacement, with the draft firstly being averaged between the port ($draft_p$) and starboard ($draft_s$) side at each location (Equation 1), and then averaged across the ship to minimise errors due to vessel hog or sag (Equation 2), resulting in what is known as the quarter mean draft (Dibble & Mitchell, 2009).

$$draft = \left(draft_p + draft_s\right)/2 \quad (1)$$

$$quarter\ mean\ draft = (draft_f + 6 * draft_m + draft_a)/8 \quad (2)$$

Once the quarter mean draft is known, this can be used to determine the volume of the vessel underwater (V), and by multiplying this by the density (ρ) of the water one can obtain the mass of water displaced (m, Equation 3). Archimedes' principle then equates this displaced water mass with that of the vessel, giving the vessel displacement.

$$m = \rho V \tag{3}$$

In practice, accurately determining the submerged volume of the vessel is not trivial due to the complex shape of the hull and so each vessel comes equipped with a precomputed hydrostatic table that equates the quarter mean draft with a displacement, generally for both sea (~1.025 g/cm^3) and fresh water (1 g/cm^3) densities.

This process to determine the vessel displacement is performed multiple times during cargo transfer operations, at a minimum at both the start and end. By taking the difference of the displacement measured at these two times and making allowances for ballast operations and other transfers to/from the vessel, the amount of cargo transferred can be determined, as shown in Equation 4.

$$m_{cargo} = disp_{end} - disp_{start} - allowances \tag{4}$$

While some automation has been added to this process as computers have been introduced, with spreadsheets or dedicated programs generally used for performing draft corrections and displacement calculations, the main time sink of the surveyor physically reading the draft marks has remained the same for hundreds of years (United Nations, 1992). Unfortunately, this step places the surveyor in potentially hazardous situations, with mooring lines and cranes often near the draft marks, and so cargo transfer operations will be paused during this time to help minimise these risks, but at the trade-off of more time at berth. There is also the variable human element involved in the reading process, with different surveyors potentially giving differing values. Being able to automate this step would remove these issues and potentially allow for continuous loading operations while vessels are at berth.

1.2 Artificial Intelligence and Computer Vision

Computer vision (CV) is a field of research concerned with using computers to analyse images and extract information from them, which can then be used to inform other decisions. Early methods were heavily reliant on image processing to identify edges and then construct simple shapes but were limited in identifying more complex objects. The rise of artificial intelligence (AI) in the 2010s led to deep learning methods, which instead use artificial neural networks (ANNs) to extract features from images, with identification being limited to the types of objects the ANN was trained upon (Ren et al. 2016). To achieve this greater flexibility, far more computing resources are required, but with the technological improvements to graphics processing units (GPUs), which are now designed to efficiently run ANNs, these models can be run at large scale, either locally or in the cloud.

Broadly speaking, there are four methods of recognising objects with computer vision (He et al. 2018). Illustrated in Figure 1, these are:

- Image classification, where the object classes present in the image are identified.
- Object detection (Figure 1b), where each instance of an object is given a bounding box for its position.
- Semantic segmentation (Figure 1c), where each pixel in the image is assigned to an object class.
- Instance segmentation (Figure 1d), where object detection and semantic segmentation are combined, assigning each pixel to unique instances of each object class.

By using these computer vision techniques, if a live camera feed of a vessel’s draft marks were available, an ANN could be trained to recognise the draft marks and report the draft in real time, preventing the need for surveyors to manually view each mark. This problem is solved by OMC International’s Optical Draft Intelligence Network (ODIN) technology (patent pending), which observes the draft marks through a combination of cameras and LiDAR devices, continuously providing the draft of a vessel times while it is at berth. ODIN is a passive system that is completely port based, imposing no further restrictions on vessels than those required for a traditional draft survey, and so can be used with all vessels.

2. Data Collection

To determine the quarter mean draft of a vessel, the draft of all six draft marks must be obtained. A typical ODIN installation will do this by using cameras installed on a wharf to provide a real time video stream of the wharf side draft marks, to which we can apply computer vision to determine the wharf side draft. Obtaining the opposite side draft marks is more difficult, as these may be facing out to sea, where no hardware can be installed, or backing on to a channel, where you will have passing vessels or possibly other berths. Wharf side LiDAR sensors are therefore used to precisely measure the vessel’s angle of list, from which we can obtain the opposite side draft marks using trigonometry.

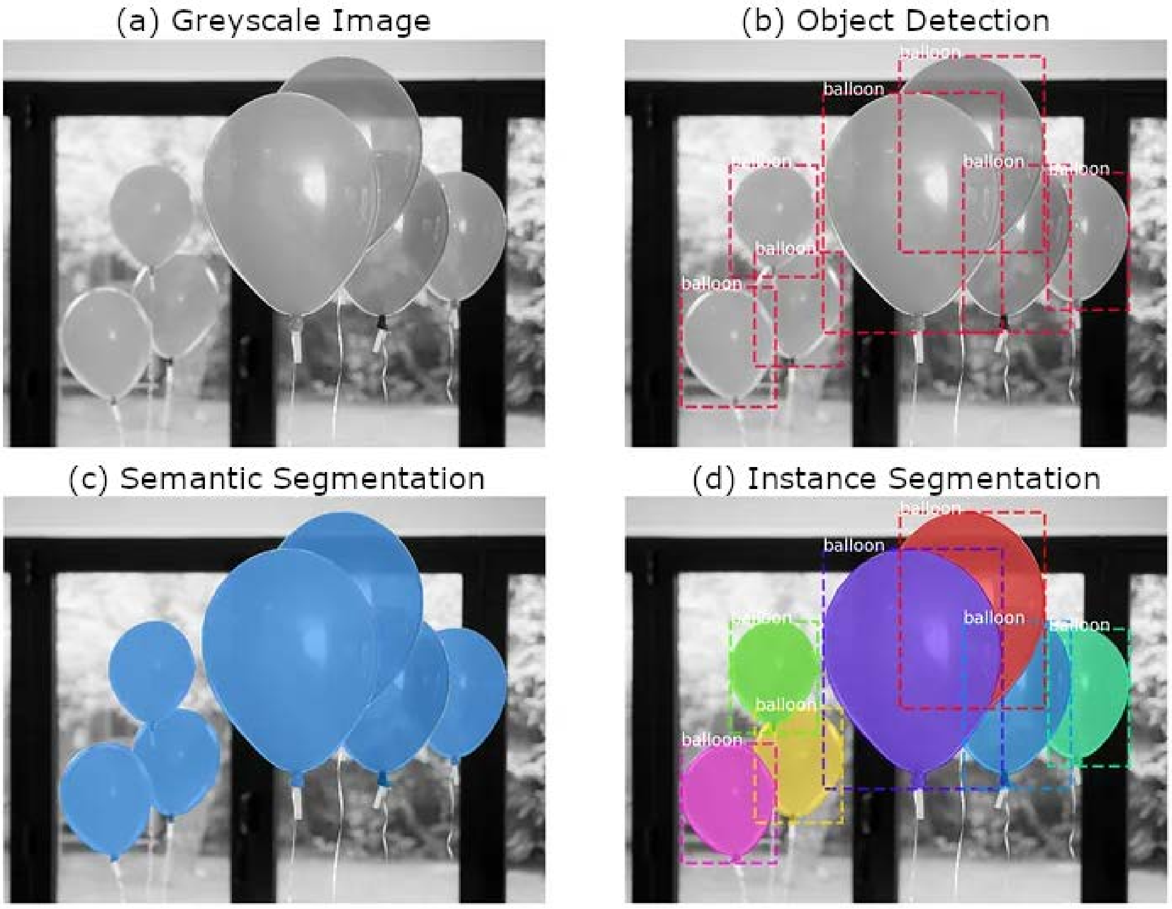

Figure 1 Illustration of computer vision methods, demonstrated on an image of balloons. Showing the original image (a), object detection (b), semantic segmentation (c), and instance segmentation (d). Adapted from Abdulla (2018).

As the length of cargo vessels can range significantly depending on vessel class, sensors must be carefully placed across berths to capture all necessary information. Choosing these locations is a complex process that must consider the following factors:

- The existing wharf infrastructure (fenders, dolphins, etc.) that may block view.
- Where vessels are aligned with the wharf.
- Variations in draft mark location on vessels.
- Minimum and maximum effective distances for each sensor.
- Lighting and environmental conditions.
- Access to power and network utilities.

As such, each berth will have a custom setup to ensure all draft marks can be determined, possibly with multiple sensors for some locations. Figure 2

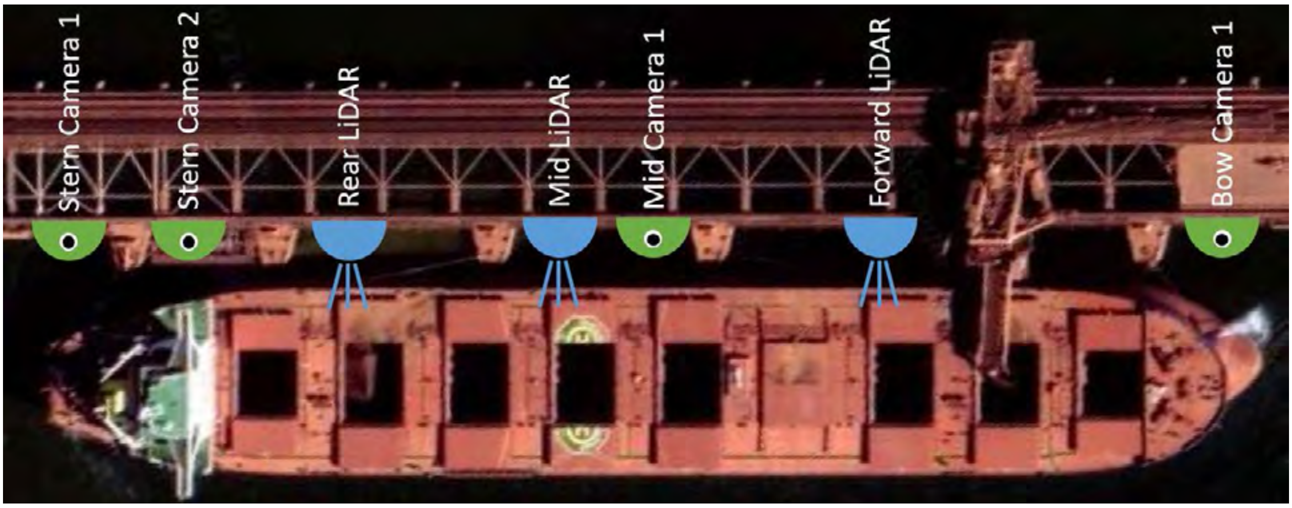

Figure 2 Example berth layout of ODIN sensors, with cameras shown in green and LiDAR shown in blue. Two stern cameras are required to ensure the stern draft marks can always be viewed around the stern mooring dolphins.

shows an example berth layout, requiring four cameras and three LiDAR sensors to accurately capture all draft marks.

2.1 Cameras

Cameras are the primary data collection device for ODIN, providing a real time stream of video data of the wharf side draft marks of a vessel. By using cameras, the fundamental process of visually observing the draft remains unchanged, with a computer now interpreting the visual instead of a person. Additionally, the recorded video feed can assist in validation if there are ever any queries about ODIN results.

As all vessels are different and never align at berth in the same location, cameras must support pan, tilt, and zoom (PTZ) functionality and not be fixed to one viewing angle, allowing the device to rotate and zoom to the correct orientation to view the draft marks. Continual camera adjustments are required throughout the time a vessel is at berth as it rises and falls with the tide, and if there is any lateral movement along the berth.

2.2 LiDAR

Light detecting and ranging, abbreviated to LiDAR, is a method for determining distances by shooting a target object with a laser and measuring the time it takes for the reflected light to return. By using a mirror rotating in one dimension to angle the laser, a scan can be made in a line, allowing for a 2D plane to be constructed, while rotating in another orthogonal dimension allows for a 3D scan to be taken.

For use in ODIN, LiDAR sensors are mounted on the wharf to take a vertical scan of the vessel hull. They are mounted more toward the centre of the vessel where the freeboard is flat, as opposed to near the bow or stern where there is more curvature, to ensure the list is accurately calculated. Multiple sensors will generally be installed, allowing the list along the vessel to be determined, which can also be used to show torsional rotation of the vessel.

3. Data Processing

3.1 Reading the wharf side draft

The wharf mounted cameras provide a constant video stream, which is made up of HD images at 25 FPS. To determine the draft in each frame, the below steps are followed, shown in Figure 3.

1. The image is sent through a CV model that performs object detection to identify the draft marks and their locations.
2. A draft ruler is created by fitting a line through the identified draft marks.
3. The image is sent through another CV model that performs instance segmentation to identify the water and the vessel. The waterline on the hull is extracted from this.
4. The intersection of the draft ruler and the waterline is found. The value of the ruler at this point is the draft for this image.

This processed is repeated continuously while a vessel is at berth, reading the latest available frame from the camera once the previous has been processed. With current processing

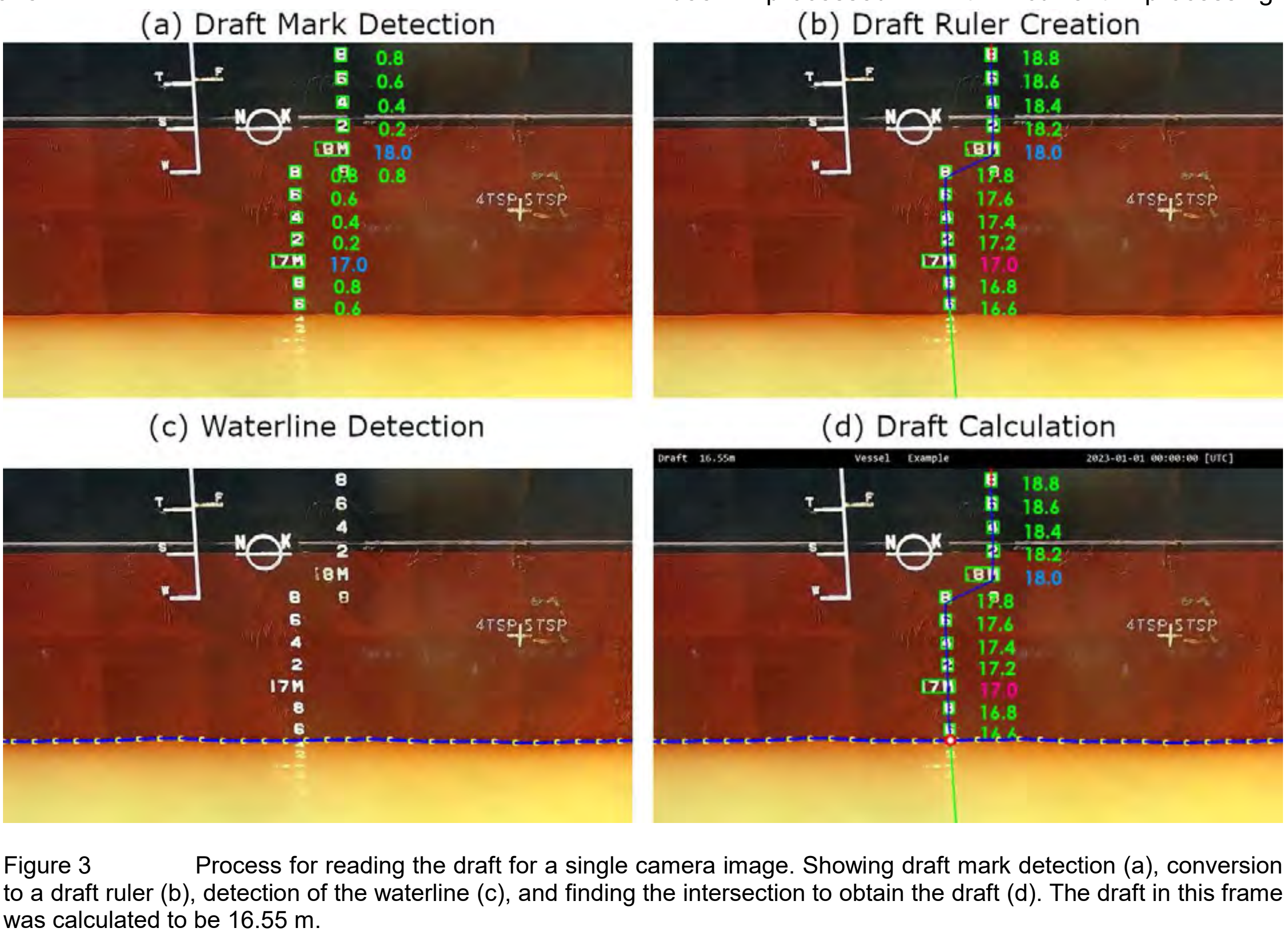

Figure 3 Process for reading the draft for a single camera image. Showing draft mark detection (a), conversion to a draft ruler (b), detection of the waterline (c), and finding the intersection to obtain the draft (d). The draft in this frame was calculated to be 16.55 m.

algorithms and hardware, a real time processing speed of 5 FPS is achieved, which will increase as hardware becomes more efficient and faster ANN models are developed.

To achieve the necessary accuracy from the CV recognition of the draft marks and waterline, the ANN models require extensive training. This is initially performed by humans manually annotating images (known as supervised training), drawing bounding boxes around each draft mark and assigning them a label, and by masking out the water. These annotations must be highly accurate, as any errors, such as labelling a draft mark incorrectly or not having a tight enough bounding box, can result in the ANN model returning bad observations. This training process is done on thousands of images, for a wide variety of vessels, time of day, and camera angle, to ensure the model can read an image in any conditions. Once a model has been created, further training can be done in an unsupervised manner, where the model will train and refine itself, with a human still involved to ensure the unsupervised training is successful.

3.2 Calculating the opposite side draft

Occurring simultaneously while the wharf side draft is being calculated, the LiDAR sensors are constantly scanning the vessel hull to determine the angle of list. Depending on the model of sensor used, more than fifty scans per second can be taken, each comprised of thousands of returns from the hull, as shown in Figure 4. These are oversampled and trimmed to ensure that only the freeboard is analysed, to which a mathematical regression is applied to calculate the line of best fit. The deviation of this from the vertical gives the list of the vessel at that point, with list to the starboard side being positive.

With the wharf side drafts ($draft_w$) and the vessel list known, the opposite side drafts ($draft_o$) can be calculated using trigonometry, shown in Equation 6. The vessel width at each set of draft marks is a configurable input if known, with default factors relative to the beam (which can be retrieved automatically from AIS messages) setup for different vessel classes if not provided.

$$draft_o = draft_w + width * \tan(list) \quad (6)$$

Applying Equation 6 to each set of draft marks allows all six draft marks to be determined, and hence the quarter mean and maximum drafts can be calculated for use in displacement and UKC calculations. Figure 5 shows the result of this process, displaying annotated frames and the draft history for a wave event while a vessel was at berth.

While draft and list are the main outputs of this processing, several other parameters can also be determined from the data collected. These include:

- Trim, the difference in the bow and stern drafts.
- Hog/sag, the difference of the bow and stern drafts compared to the mid draft.
- Drift from berth, as the LiDAR calculates the distance to the vessel.

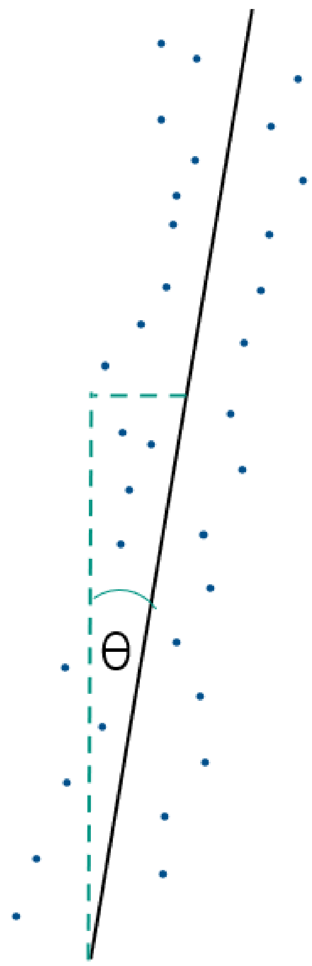

Figure 4 Pictorial example of a LiDAR point cloud that is obtained when scanning a vessel hull. Distance between points has been exaggerated for display. A line of best fit is calculated, with the angle of deviation from the vertical, θ, giving the vessel list.

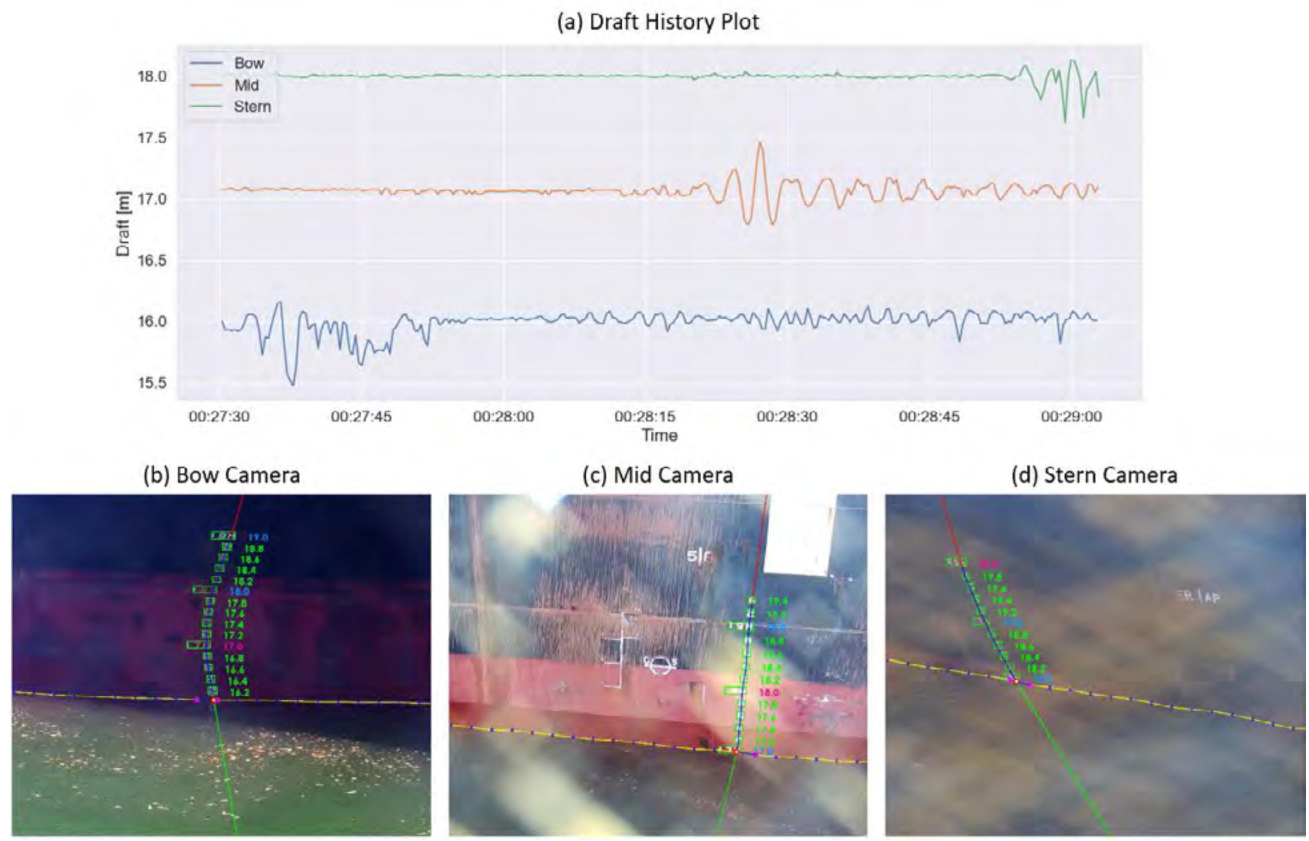

Figure 5 (a) Time history of vessel draft during a wave event. Draft has been averaged between the port (observed) and starboard (calculated) draft marks. (b), (c) and (d) show the annotated camera images at 00:28:29.

3.3 Limitations

As with any automated computer system, ODIN does have limits under which it can operate. In particular, if the cameras cannot record a good quality image of the draft marks, poor readings are likely to result. Examples of scenarios that can cause this, along with methods of remediation, are listed below.

- Draft mark obstruction. If obstructed by temporary objects, such as cable washers, these may need to be moved for a time when a draft reading is required. If obstructed by permanent objects, alternate camera locations may be required.
- Draft mark fouling. If the draft marks are unable to be read by a human, ODIN will also have similar issues, with an example shown in Figure 6. In this case, the vessel should clean and repaint the draft marks, allowing for them to be read again and ensuring compliance with Australian Maritime Safety Authority (AMSA) regulations (AMSA, 2016).
- Poor lighting, generally at night. Wharf mounted lights may need to be installed to ensure the draft marks are clearly illuminated.
- Camera alignment, particularly around the curvature of the hull on some vessel classes at bow and stern. Additional cameras at better locations may be required to ensure the draft marks can be clearly viewed.

Figure 6 Fouled draft marks on a vessel. The marks from 9.4 m and lower are covered by rust and marine life, rendering them unable to be read at a distance.

Another limitation of the system is the type of draft marks that ODIN has been trained on. As of 2023, ODIN has been trained to recognise two formats of metric system draft marks, viewable in Figure 7. To be able to interpret other formats (such as the imperial system), further training of the ANN models would be required.

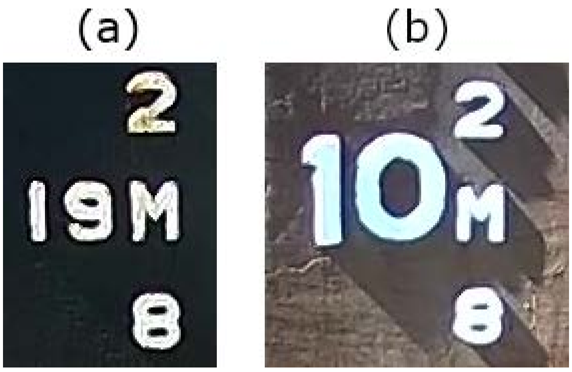

Figure 7 Metric draft mark formats that ODIN has been trained to interpret. (a) shows draft marks where the meter digits are 10 cm in height, while (b) shows draft marks where they are 20 cm in height.

4. Data Usage

To make use of the information provided by ODIN, a web interface is provided to users, allowing access from anywhere with an internet connection. The interface provides both a live view of the current vessel at berth, as well as historical views to see what happened with previous vessels. Time series plots of the draft are displayed, along with annotated images and videos of the vessel. Reports can be generated to provide a summary of a vessel at a point in time, while raw data can be exported for further analysis if desired. Alerts are also able to be created if any parameters fall outside configured bounds.

The ability to integrate ODIN with other products or services is built into the system, with various APIs available that can provide both live and historic data for needed use cases. These may include other systems such as automated ship loaders, which need to know the draft in real time to ensure they are loading the correct amount of product into a cargo hold.

Depending on the existing method draft surveyors use to do their surveys, draft information from ODIN may be either manually entered or retrieved automatically via the API for use in the calculations. As the other necessary information for completing a draft survey is either vessel specific (hydrostatic tables) or changes with each visit (tank soundings), ODIN is currently unable to perform the full process and determine the amount of cargo on board. As vessels become increasingly fitted out with technology, live feeds for these may be available in the future, allowing ODIN to perform the entirety of the draft survey process.

5. Conclusions

We have demonstrated the ability to remotely obtain the draft of a vessel from all six draft marks, without requiring a human to be involved. Through a combination of cameras and LiDAR devices, ODIN provides an uninterrupted, real-time feed of the draft, with accompanying images and videos giving confidence to users in the numbers they receive. Several other parameters are also obtained, such as list and trim, with a web interface and API exposing all of this for usage by humans and other systems.

By removing the need for surveyors to read the draft marks, they no longer need to enter hazardous areas around the vessel to perform their job, improving safety and allowing them to instead get the draft in seconds instead of hours. Cargo transfer operations also no longer need to be stopped during this process, potentially allowing vessels to depart hours earlier.

While ODIN is for now limited to just determining the draft, it is envisaged that in the future it will be able to do the entirety of the draft survey process as vessels become more equipped with technology, eventually allowing for a real-time feed of cargo on a vessel throughout the entirety of a stay at berth.

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