Automated System for Ship Draught Measurement with Component of Intelligent Systems

S. G. Chernyi [I, II], A. N. Ivanovskii [I]

[I] Kerch State Maritime Technological University, Kerch, Russia
[II] Saint Petersburg State Marine Technical University, Saint-Petersburg, Russia

Abstract. Knowing ship draught is vital for calculating cargo mass onboard of marine vessel. Even small error in its measurement can lead to significant loss of cargo. Although many tools and methods for ship draught reading have been developed, none of them can provide sufficient accuracy. Also, every known method assumes human participation in measurement process. To eliminate the human factor, we propose to develop automated system which will provide sufficient for practical needs accuracy. It includes UAV with digital camera based on it, ship clinometers and computing section. We consider a method, based on processing of draught marks video with neural networks. YOLOv5 convolutional neural network has been used for digits detection, and U-Net convolutional neural network for segmentation of water surface area on each frame. Of note, we look over the concept of ship draught in term of stochastic process and took into account ship heel and trim, as they significantly affect the final result.

Keywords: UAV, intelligent, ship draught, neural networks, YOLOv5, U-Net.

DOI 10.14357/20718632220207

Introduction

The ships draught is the vertical distance between the waterline and the bottom of the hull (keel). As ship has heel, trim, hogging or sagging, it's obvious, that in different points of the vessel it has different values. However, on practice it's convenient to have single constant value and use it as initial parameter in hydrostatic tables. Hence, hereinafter we can declare two base definitions. Measured draughts – are real draughts, that usually observed on pre-defined key points on the port and starboard sides forward, midships, and astern. Estimated draught, or mean draught – is averaged value of measured draughts, used in calculations.

The degree of demand for knowledge of draught on different ships varies. For container ships, tankers, passenger ships, it is needed mainly for passage planning and navigation in narrows and channels. Therefore the installation of bulky high-precision systems for measurement doesn't have sense. On bulk carriers the draught value is used for calculating amount of cargo onboard, so accuracy of gages directly affects the profits of concerned parties.

Depending on the equipment used, there are five main ways to determine the draught:

– visually (sensor - human eye);
– by hydrostatic pressure (sensor - hydrostat);
– using GLONASS / GPS equipment;
– using ultrasonic sensors;
– using digital camera with image processing software.

Despite the variety, in practice only a visual method is used, the accuracy of which depends on the cargo officers' experience. The rest of the methods, as a rule, require significant re-equipment of the vessel, are difficult to operate, while not providing sufficient measurement accuracy, even with light breeze. It should be noted that an ultrasonic survey tool might be the best solution for calm weather. However, bulk carriers are often loaded at anchorage and affected by wind, current, strong swell, rolling and pitching, so pointed methods become inapplicable.

Draw attention, that the measured draughts are stochastic processes, which depend on the environment conditions and ship state. All known methods use a simplified approach to measurement data processing, which inevitably leads to significant errors and makes it impossible to provide adequate estimation and evaluate the effectiveness of such methods.

All of the above necessitates us to revise the existing approach to determining the draught, as well as to develop solution for draught survey tool, that meets a number of criteria:

– Easy to install and maintain.
– Applicable in all weather conditions without significant loss of accuracy.
– Has proved data processing algorithm.
– Minimized human factor.
– Affordable price.

In our view, image-processing based methods have the best prospects for meeting these criteria. To use them we need just digital camera and computer, that makes it really accessible. Its accuracy is limited only by resolution capability of camera. It is easy to gather and analyze data as we work with digital signals. As for human factor, known solutions involve the control of the image processing by a qualified computer vision specialist. It can be rectified by replacing computer vision modules (CV) by convolutional neural networks (CNN).

1. Relevance

1.1. Draught Survey

The main method for determining the mass of cargo on bulk carriers is a draught survey. The procedure is standardized by 1, according to which the recommended draught survey accuracy is 0.5% of the cargo mass onboard. It is based on Archimedes` principle and weight of cargo is calculated by difference between ship displacements for the arrival and departure [2]. To determine it we can use the following formula:

$$M_{cargo} = (Disp_2 - \Sigma_{bunk2}) - (Disp_1 - \Sigma_{bunk1}), \quad (1)$$

where M_{cargo} – is mass of cargo (loaded or discharged); $Disp$ – ship displacement for arrival and departure respectively, that can be obtained from hydrostatic tables by mean draught and sea water density; Σ_{bunk} – ship bunkers. Index 1 or 2 refer to arrival or departure, respectively.

$$\Sigma_{bunk} = P_{fuel} + P_{oil} + P_{f.water} + P_{ballast}, \quad (2)$$

where P_{fuel}, P_{oil}, $P_{f.water}$, $P_{ballast}$ – are masses of fuel, oil, fresh water, ballast water and crew stores.

$$Disp_1 = D_0 + \Sigma_{bunk1} + const, \quad (3)$$

$$Disp_2 = D_0 + \Sigma_{bunk2} + M_{cargo} + const = D_0 + DWT, \quad (4)$$

where D_0 – is light ship weight, DWT – deadweight, *const* is ship constant, which is result of accumulation of ship stores, corrosion, dirt, fouling of hull, coating build-up (paint work, tank coatings), sedimentation in ballast or fuel oil tanks etc. Ship lightweight includes the ship and its full equipment, engine room spares, water in the boiler and the lubricating oil in the engines. Generally, it increases over time (by about 0.5% per annum), particularly for ships which are prone to corrosion and don't undergo regular maintenance. Such increment is also a part of ship constant value. Often, crew mass is considered as separate summand, but on practice it's reasonable to include it in a ship constant, since it is hard to measure.

1.2. Draught Survey Errors

Let us evaluate errors, which can occur while calculating the mass of cargo. As an illustrative example, consider the bulk carrier Universal Bangkok, with given initial parameters: $Disp_{max}$*=67,681 tons*, DWT *= 56,793.8 tons*, $\Sigma_{bunk.max}$ *= 19,636.7 tons*, D_0 *= 10,941.2 tons* 3.

Mass of ship bunkers can be measured with sensors of some type, or manually using dipping tape. For the vessel under consideration with error of *0.1%* of liquid mass we can potentially loss Δ_{bunk} *= 20 tons* of cargo (*0.03%* of total maximum cargo onboard). Generally, such error can be even less.

Ship lightweight is known from cargo manual, but it increases over time (by about 0.5% per annum), particularly for ships which are prone to corrosion and don't undergo regular maintenance. It is caused by accumulation of ship stores, corrosion, dirt, fouling of hull. All these changes are entered into the ship's constant. From formula (3) it follows that the constant is calculated as:

$$const = Disp - D_0 - \Sigma_{bunk} \tag{5}$$

Displacement error (Δ_{disp}) depends on sea water density error (Δ_{dens}) and draught measurement error ($\Delta_{draught}$). Correction for seawater density is determined by the formula:

$$\Delta D_{dens} = Disp\frac{\rho_{table} - \rho_{measured}}{\rho_{measured}}, \tag{6}$$

where ρ_{table}, $\rho_{measured}$ – are sea water density, used in hydrostatic tables and measured by hydrometer accordingly. The error in measuring the density of water is half a division of the hydrometer scale, that is, 0.5 kg/m3. Finally:

$$\begin{aligned}\Delta_{dens} &= Disp\frac{\rho_{table} - \rho_{measured} + 0.5}{\rho_{measured}} - \\ &- Disp\frac{\rho_{table} - \rho_{measured}}{\rho_{measured}} = \frac{Disp}{2\rho_{measured}},\end{aligned} \tag{7}$$

which is $\Delta_{dens} = 33tons$ (0.058% of cargo mass) for chosen ship.

With the maximum load of the vessel, one centimeter of its draught accounts for 58.7 tons of displacement. That means we can loss $\Delta_{draught} = 0.1\%$ of cargo mass on each centimeter. In bad weather conditions, even an experienced officer is capable of making an error in draught gaging of 5 centimeters or more (with responsive increase of $\Delta_{draught}$ up to 0.5%). Total error of draught survey become:

$$\Delta_{survey} = \Delta_{bunk} + \Delta_{dens} + \Delta_{draught} = 0{,}588\%, \tag{8}$$

and already exceeds recommended error of 0.5%. As we need to calculate displacement both on arrival and departure, this error just doubles and become 1.176% of cargo mass. For the sake of clarity, it is 668 tons of potentially lost cargo, that costs dozens of thousands of US dollars and caused by objective factors.

2. Draught Reading with Machine Learning

2.1. Existing Methods Comparison

Comparison of methods, noted in introduction is presented in Table 1.

Errors are indicated in absolute terms. Loss of cargo in this case will vary for different vessels. So, for small ships, it can reach 0.2% of the total mass, and for capesize bulk carriers it may be less than 0.05%.

2.2. Draught Marks

Each vessel has six draught marks on the sides (Fig. 1), which are the set of Arabic or Roman numerals (Fig. 2), located one above the other at equal intervals. The measured draught at each position is defined as the point of intersection of the draught mark with the water surface, and after some standard corrections the mean draught can be calculated. As we told earlier it is further used to determine the real loading condition of the vessel.

2.3. General Description of the Method

In world practice, measurements of draught are made from a boat or pilot ladder jointly by a draught surveyor and a ship cargo officer. As stated in introduction, the method is based on the use of a digital camera as a sensor to determine the ship's draught. Regardless of the way used to obtain the video recordings, the video is transmitted to a central computer, where it is processed by machine learning algorithms.

Table 1. Methods comparison

Method	Accuracy	Crucial factor
Visual	5 cm	Officers experience
Measuring pipe with dampers	3 cm	Officers experience, unsuitable for swell
By hydrostatic pressure	1,5% of draught	Difficult installation and the lowest accuracy
GLONASS / GPS antennas	2 cm	Unsuitable for swell, low accuracy
Ultrasonic sensors	0,1 cm	Unsuitable for swell
Computer vision	0,5 cm	Need software tweak, subjected to noise

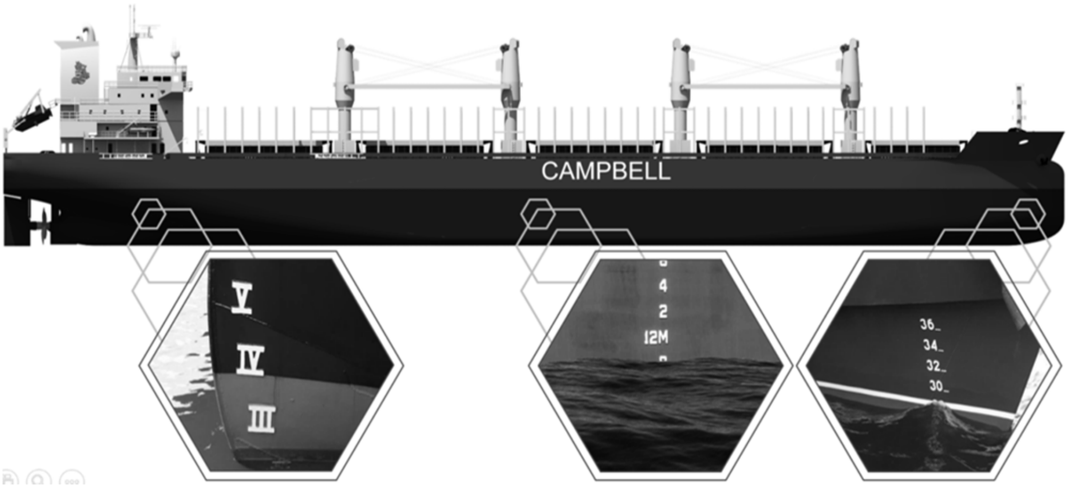

Fig. 1. Position of draught marks and their appearance

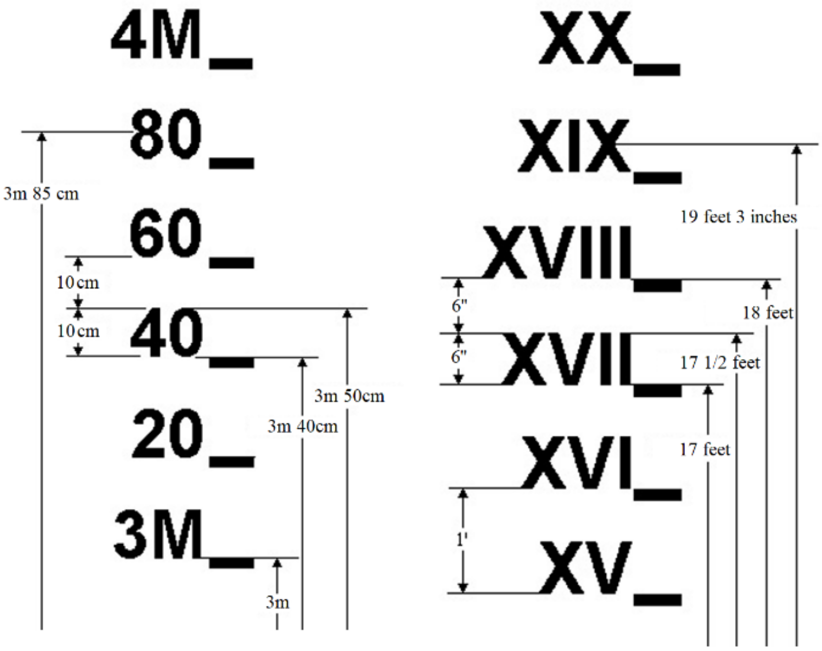

Fig. 2. Draught marks templates

Fig. 3 describes the general structure of the technological process for determining the ship draught by video recordings of draught marks. In addition to another method of making measurements, an important part of the algorithm is time synchronization with ship's inclinometers. This allows us to make corrections to the measurements for roll and trim, which in some cases reach dozens of centimeters (with the target accuracy of 1 cm and less), and are not taken into account in any of the known methods of draught reading.

Firstly, we take a video recording of the draught mark intersecting a water surface as an input. After frame-by-frame processing with machine learning models we get an array of measured draughts. Next, this array should be checked for outliers and if the test passed, we can add correction for heel and trim and process the final array with linear filter. Such procedure should be repeated six times for every draught mark on the forward, midship and aft. Algorithm ends when all the data logged and we obtain the estimated draught as an output.

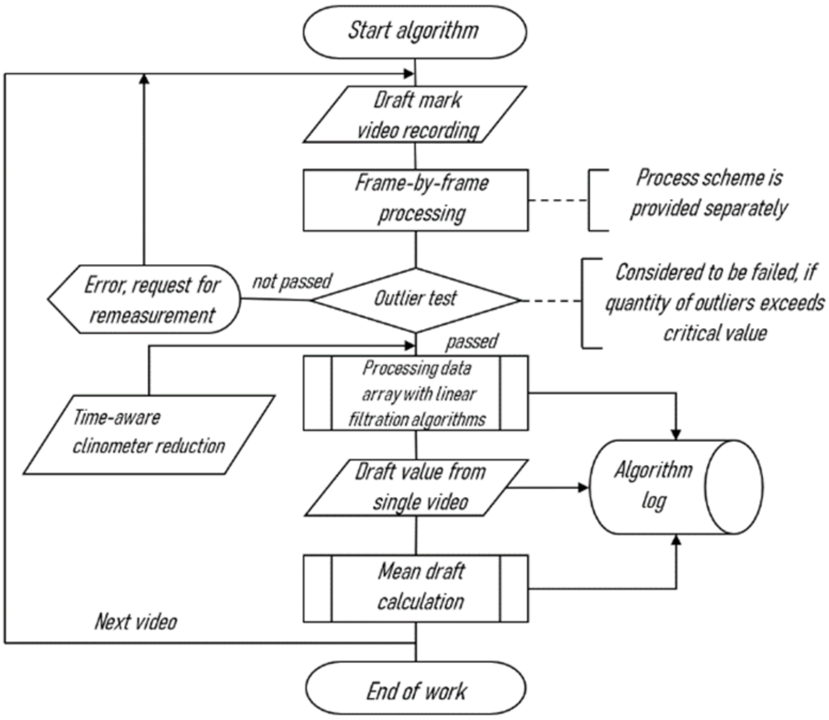

Fig. 3 Algorithm for determining the ship draught based on machine learning methods

Frame-by-frame video processing is a key algorithm, that consists of machine learning and computer vision models, which makes it possible to measure the draught at the current time (Fig. 4). It has three base operations: detection and identification of draft mark digits; water surface segmentation; calculate reference axis and compute an intersection point, which is measured draught. We loop procedure while there are frames in video. The choice of video duration is justified experimentally by processing samples of various length. So, generally a video of one-minute duration corresponds to an array of 1800 values of draught at 30 frames per second and is enough to gather sufficient amount of data. It also provides logging of data that can be used in case of any litigations between concerned parties.

A further increase in accuracy is possible by increasing the accuracy of single measurements, as well as improving digital filters used for data processing.

2.4 Detection the Draught Mark

To date, there are already works devoted to the use of computer vision and machine learning for ship draught measurement [4, 5, 7, 9-11]. Such methods are effective under favorable weather conditions, but often vessel is operated at the anchorage and subjected to wind, swell, tides and currents. The process of taking measurements can also be complicated by the boat rolling, on which there is a person with a camera, the presence of fog, rain and lighting conditions. Therefore, for the successful application of computer vision algorithms, their careful adjustment is required in each individual case. Such tuning includes noise removal, selection of binarization parameters, tuning and evaluation of the descriptor efficiency.

In addition to time-consuming, determining the draught in this way requires a high qualification of the cargo officer in the matter of computer vision algorithms. It is obvious that in the real conditions of the ship operation, the using of classical methods of computer vision is impractical. In order to reduce the effect of noise on the processing results, eliminate the human factor and optimize the time of measurements, it was decided to implement the method using CNN.

When choosing CNN architecture, we were guided by the results of the International Conference on Document Analysis and Recognition (ICDAR Competition on Robust Reading) 2015 6, as well as

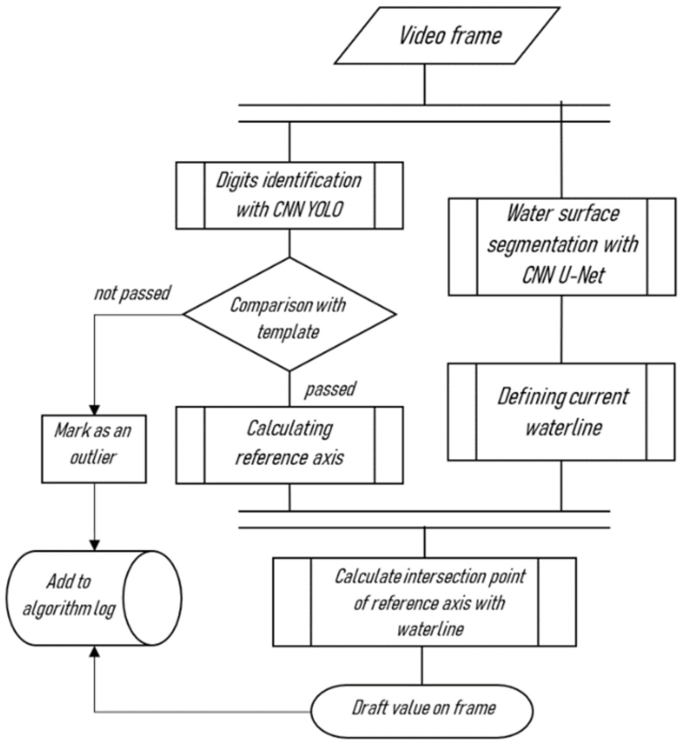

Fig. 4. Algorithm of frame-by-frame draught mark video processing

publications from the list 8, however, many of the presented methods are more suitable for recognition of a large volume of text prepared in advance, and also do not exclude the possibility of additional customization by a person. Our task is to identify only ten different numbers and the letter "M", while determining the coordinates of the numbers is just as important as identifying them.

Based on the above-mentioned reasons, it was decided to work with images in context of object detection, not text search. To solve this problem, there are a number of methods, most of which involve the application of artificial neural networks to an image or video sequence. Based on the results of the effectiveness of various neural networks in other tasks of detecting objects in the image, and also taking into account that to determine the ship's draught it is necessary to process large arrays of images (up to 10,800 images or more in one draught survey) in real time, it was decided to use neural networks of the YOLO architecture, particular YOLO v5. The indisputable advantages of this CNN include the speed of its operation (up to 60 frames per second), small size (up to 250 MB), as well as low requirements for computing power.

For training the YOLO v5 CNN, a database of 32 draught marks videos was collected from ships located in the roadstead of the Kerch Strait and bulk carriers of the world fleet. The neural network was trained to recognize 11 classes, including ten numbers and the letter "M". For this, 1,200 images were marked up, on which 9,210 annotations were allocated. The Roboflow service was used to mark images. For data augmentation, three types of affine transformations (shift, stretch, rotation) were used, as well as image noise, and as a result, the original sample was expanded to 6,000 images.

The input of the neural network is 640x360 image, at the output we get a list of rectangular areas with the coordinates of the vertices, as well as the classes to which these regions correspond. To estimate the accuracy of the detector we used mAP (mean Average Precision) metric, which is commonly used while training CNN. The mAP compares the ground-truth bounding box to the detected box and returns a score. The higher the score, the more accurate the model is in its detections. After 150 epochs of training, we have reached mAP of 72.4%. The graph of the dependence of the mAP metric on the number of epochs is shown on Fig. 5. This is due to

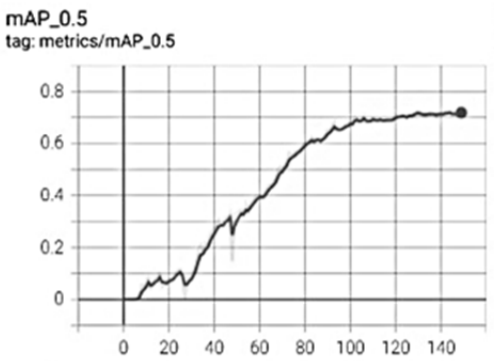

Fig. 5. YOLO v5 accuracy assessment

the fact that the training of the CNN was carried out only on video recordings of real ships, most of which have draught from 8 to 12 meters and digits “0”, “3”, “5”, “7” are not enough represented.

We can increase mAP by training CNN on generated images with missing digits. The highest result that we achieved is mAP of 93.9%, that is good result and proves possibility of using such approach on practice. To further improve the quality of the neural network operation on real images, it is necessary to increase the proportion of rare classes in the training sample.

An example of how YOLO v5 works on a test image is shown in Fig. 6. It allows to detect digits on the frame and represent the probability of their belonging to certain class. As a result we get the list of rectangles with their coordinates and class.

Knowing the location of the draught mark digits and their real size on the ship's hull (the height of each letter is 0.1 m), we can build a coordinate scale. The numbers next to the "M" are taken as reference points. So, for example, if "M" is next to "8", then the center of the rectangle with the letter corresponds to the draught value of 8.05 meters. Then, we check the order of the numbers in the entire image according with template in figure 2. It is necessary to recognize erroneously identified numbers and fill in the gaps, if some numbers are not found at all.

At the centers of the obtained rectangles, using the least squares method, we can build a coordinate line. We can use it to determine the scale of the image and the maximum accuracy of each specific measurement. An example of such a construction is shown in Fig. 7. In the version that is shown one pixel of the image corresponds to 0.0035m, which is also the limiting accuracy of this measurement.

Fig. 6. An example of determining the draught mark digits in a noisy image

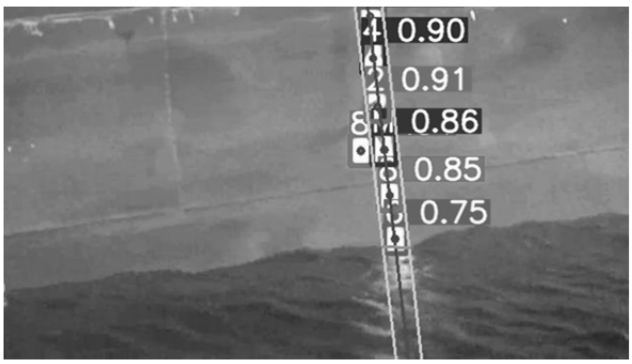

Fig. 7. Reference axis on the image calculation and visualization

2.5. Water Surface Segmentation

After constructing a coordinate scale linked to the digits of the draught mark, we need to determine the point of intersection of the groove mark with the waterline. In other words, we are faced with the task of defining the boundary of the water surface. There are many ways to define boundaries, in particular, the Kenny, Sobel, Pruitt, Sharr, Roberts operators are classical. Like many other computer vision algorithms, this set of detectors requires careful adjustment of the bunch of parameters. Depending on the setting, image noise conditions, lighting conditions, detectors can find both excessive and insufficient edges in the image.

Based on the above reasons, it was decided to segment the water surface instead of finding its outline. So, it is proposed to divide the image into two classes - "water" and "not water" (ship hull, sky, various objects in the frame). It is no longer necessary to segment the draught mark in the image, as it was done in the previous step.

As a replacement of computer vision, it is also proposed to use CNN. The most common CNNs for image segmentation for now are R-CNN, FCN, U-Net and ASPP. In our case, it was decided to use a neural network of the U-Net type, because it is suited for dividing an image into two classes best of all. We have an image of 640x360 pixels as input and at the output we get a mask image, where the pixels are assigned to one of two classes (Fig. 8).

By intersection of reference axis from previous step and upper boarder of segmented water surface we can get a measured draught on each frame. By repeating previous steps for each frame of draught mark video recording we obtain an array of measured draughts.

2.6. Measurements Processing

After we have gathered measurements arrays, it is time to calculate the final draught of the vessel. As we stated in introduction, the measured draught is a random process, and since we cannot measure the draught continuously it is discrete. Regardless of the method of measuring the draught of the vessel, we will assume that at the input we have a digital signal consisting of measurements of the draught for a certain period of time.

Let's proceed to the synthesis of the optimal linear filter for calculating the settlement value from the array of measurements. Let $X(t_i)$ be the value of the precipitation at the current moment of time, $Y^*(t_i)$ – measurement, $\xi(t_i)$ – is the total deviation (noise), which represents various kinds of disturbances arising under the influence of the environment. Taking this fact into account, the sought value can be represented as:

$$X(t_i) = Y^*(t_i) - \xi(t_i) \qquad (9)$$

Here:

$$\xi(t_i) = \Theta(t_i) + \Psi(t_i) + \xi^*(t_i), \qquad (10)$$

where $\Theta(t_i)$ – heel correction, $\Psi(t_i)$ – trim correction, $\xi^*(t_i)$ – centered wave function. The special attention should be paid to the usage of clinometers. As measurements of draught are planned to be time-aware and carried out with digital camera, it is

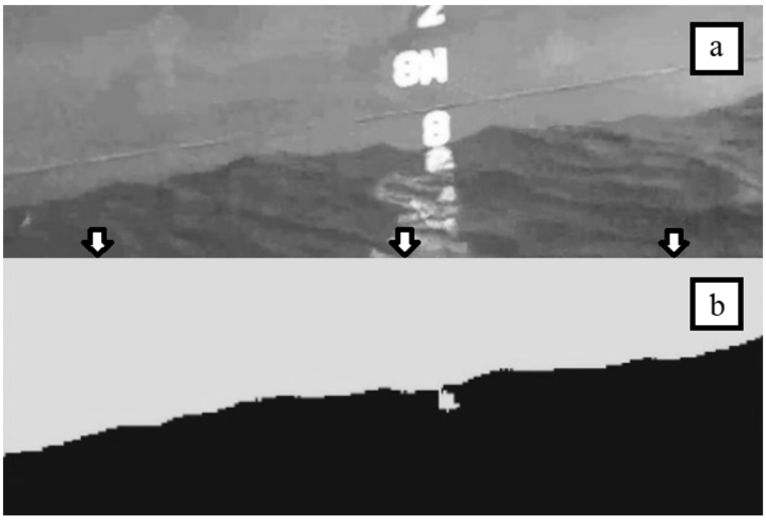

Fig. 8. Water surface segmentation with CNN U-Net, where a – original image, b – image-mask with segmented water surface

obvious that ship is exposed to pitching and rolling. Though, the ship's trim directly affects the measurements results. On the thirty meters width ship, the one-degree trim can cause reduction in twenty-six centimeters, that is huge, assuming that only one-centimeter error equals to loss of dozens of cargo tones. At present, highly precise clinometers are already developed, so they can provide accuracy of measurements up to centesimal of degree.

Taking everything into account, it is possible to synthesize a linear filter that allows to find the estimated draught by an array of measured draughts (Fig. 9).

$$\hat{X}(t_i+1)=\hat{X}(t_i)+P(t_i)\left(Y^*(t_i)-\hat{X}(t_i)\right), \quad (11)$$

where, $\hat{X}(t_i)$, $\hat{X}(t_i+1)$ – estimates of the draught value at the current and next time instant, $Y^*(t_i)-\hat{X}(t_i)=\tau$ - residual, $P(t_i)$ – residual weight.

$$P(t_i+1)=K(t_i)\left(K(t_i)+\tau^2\right)^{-1}=\frac{K(t_i)}{K(t_i)+\tau^2}, \quad (12)$$

$$K(t_i+1)=K(t_i)-P(t_i+1)K(t_i)=\frac{K(t_i)\tau^2}{K(t_i)+\tau^2}, \quad (13)$$

where $K(t_i)$ – the variance error matrix.

The estimated error is less than 1% of the wave amplitude. Need to note, that in present case the amplitude is about 60 cm and no existing method can be applied in such conditions. An important point is the hypothesis of the ergodicity and stationarity of the described random process in a short period of time (20-40 minutes, comparable to the standard time for a draught survey), since this allows to estimate the draught of the vessel from just one series of measurements.

3. Method Automatization

3.1. Automatization of Video Recording

In world practice, measurements of draught are made from a boat or launch jointly by a draught surveyor and a ship cargo officer. During the transition phase, it is also possible to take video from a boat using an electronic stabilizer with a digital camera. From the point of view of equipping unmanned vessels in the future it is proposed to unmanned aerial vehicle (UAV) for taking video recordings of the draught mark. Of course, there are some limitations due to wind and visibility, but in bad weather conditions, cargo operations are not carried out anyway.

For taking-off and landing of the drone, it is proposed to use computer vision, which allows to determine the location of the UAV station by a special visual marker. Next, the drone should fly around the vessel, descending in key positions (Fig. 10).

Draught marks search is also performed by using machine learning methods. For positioning the drone, it is proposed to use a network of transceivers, allowing to determine the distance to the UAV [12, 13]. The UAV location is determined using multilateration, by solving the system of equations:

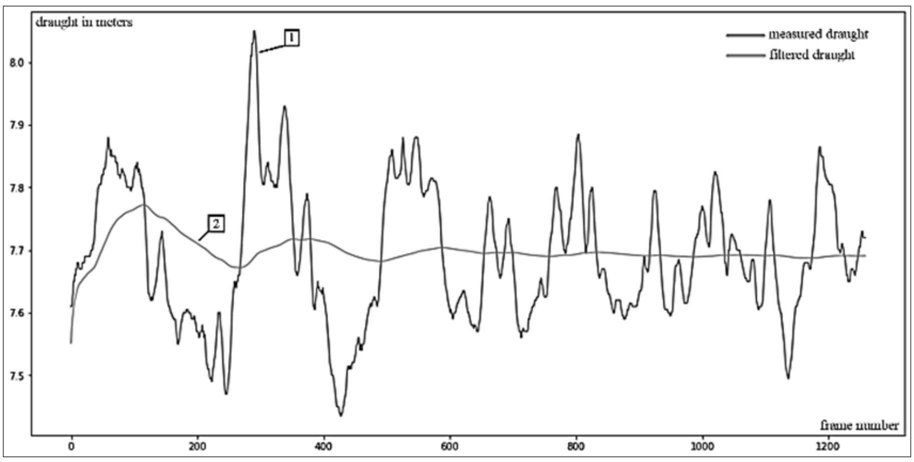

Fig. 9. Visualization of the measured draught array processing with linear filter
1 – measured draught, 2 – filtered draught

$$\begin{cases}(x-x_1)^2+(y-y_1)^2+(z-z_1)^2=R_1^2\\ \dots \\ (x-x_i)^2+(y-y_i)^2+(z-z_i)^2=R_i^2\end{cases}, \qquad (14)$$

where $O_i(x_i, y_i, z_i)$ are the coordinates of the centers and R_i are the radii of the spheres of the distances, received from the transceivers, n is the number of transceivers. Modern solutions allow to achieve an accuracy of positioning of one meter, which is sufficient for our purposes, since more precise positioning at key locations is carried out by means of machine learning.

The number of transceivers may vary depending on the size of the vessel and its design. To eliminate a number of uncertainties, we can additionally use a set of ultrasonic sensors on the drone, which will at least estimate the flight altitude of the drone above the sea surface or above the vessel [14].

3.2. Draught Measurement System Structure

The drone, in combination with distance sensors, a digital camera, inclinometers and a computer for data processing conclude an automated system for ship draught measurement. The structure of such system is shown at Fig. 11. The system is automated due to the operator's access to control the drone, if it's necessary, and it is the person who determines the start and end times of the system.

Conclusion

The creation of the proposed automated draught measurement system will increase the speed of the procedure, as well as eliminate the influence of the

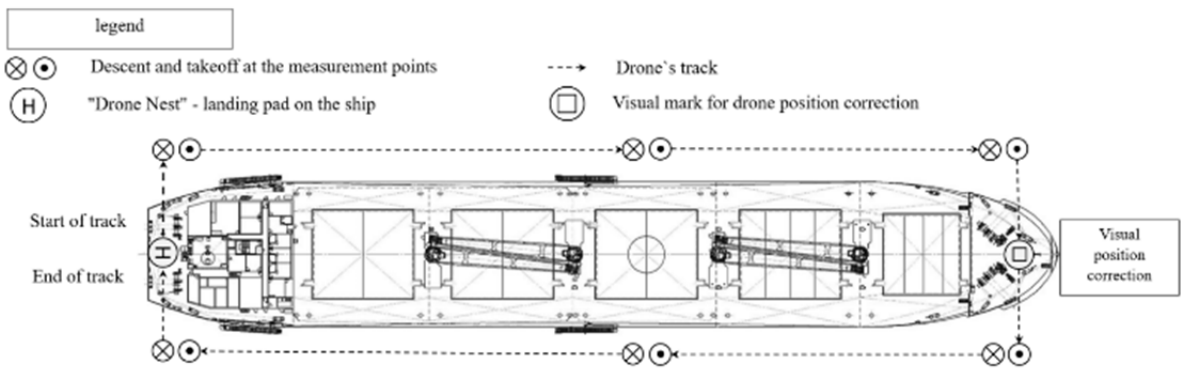

Fig. 10. Scheme of drone navigation around the ship

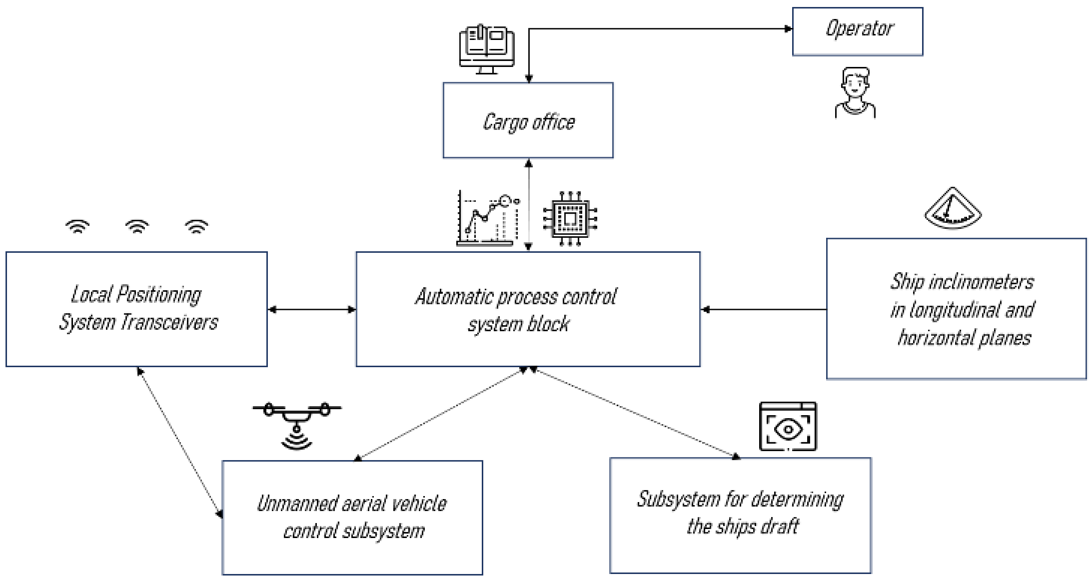

Fig. 11. Automated draught survey system structure

human factor. Based on machine learning and computer vision technologies method is universal for any type of vessel. In combination with linear filtration algorithms and ship inclinometers, this technology allows achieving an accuracy of several millimeters in draught measurement, which is significantly superior to existing analogues.

References

1. ECE/ENERGY/19 – Code of uniform standards and procedures for the performance of draught surveys of coal cargoes. Economic Commission for Europe, United Nations. 1992. – 192 p.
2. Elnoury A., Gaber E. Accuracy of draught survey process and affecting factors // International Journal of Research in Engineering & Technology. 2018. p. 19–27.
3. Final loading manual, Universal Bangkok. – Shanghai, Ref. No. 12-044531, 2012. 642 p.
4. Ferreira J., Fernandes M., Santos C., Vassalo R. Character recognition for automatic draught survey. 2018 13th IEEE International Conference on Industry Applications (INDUSCON) // IEEE, 2018. C. 332-338.
5. Gu H.W., Zhang W., Xu W.H. Digital Measurement System for Ship Draught Survey // Applied Mechanics & Materials. 2013. 312–316.
6. Karatzas D. ICDAR 2015 competition on robust reading. 2015 13th International Conference on Document Analysis and Recognition (ICDAR) // IEEE 2015. 1156 – 1160.
7. Okamoto A., Yoshida H., Tanaka N., Hirono K. A draught reading method by image processing with the robustness of measurement distance // The Journal of Japan Institute of Navigation. 2014. T. 130. p. 135–140.
8. Carlos Tao "Scene Text Localization & Recognition Resources" Internet: https://github.com/chongyangtao/Awesome-Scene-Text-Recognition, Jul. 30, 2018 [Aug. 6, 2021].
9. Tsujii T., Yoshida H., Iiguni Y. Automatic draught reading based on image processing // Optical Engineering. 2016. 55(10). 1-9.
10. Vinogradov V.N. Correlation theory of filtration and control of multidimensional random processes: Linear correlation theory of filtration and control. M.: KRASAND, 2012. – 320 p.
11. Wang, Bangping, Zhiming Liu, and Haoran Wang. Computer vision with deep learning for ship draught reading // Optical Engineering 60, 2 (2021): 024105.
12. Ivanovsky N., Chernyi S., Sokolov S., Zhilenkov A., Zinchenko A. Algorithm design for ship's steering with specified limitations under various weather conditions // Brodogradnja, vol. 72, no. 4, pp. 19-32, 2021. Available: 10.21278/brod72402
13. Yemelyanov V., Chernyi S., Yemelyanova N., Varadarajan V. Application of neural networks to forecast changes in the technical condition of critical production facilities // Computers & Electrical Engineering, vol. 93, p. 107225, 2021. Available: 10.1016/j.compeleceng.2021.107225
14. Zhilenkov A.A., Chernyi S.G., Firsov A. Autonomous underwater robot fuzzy motion control system for operation under parametric uncertainties // Journal of Information Technologies and Computing Systems. 2021. № 1. C. 50-57.

Ivanovskii A. N. Kerch State Maritime Technological University, 2983095, Russia, Kerch, Ordzonikidze st., 82. PhD student of the Department of Electrical Equipment of Ships and Industrial Automation. Number of publications: 18. Research interests: electric power industry, fuzzy system, intelligent complexes. E-mail: aleksei.ivanovskii@yandex.ru .

Chernyi S. G. PhD, Kerch State Maritime Technological University, Kerch, Ordzhonikidze 82, Russia, 298309., St. Petersburg State Marine Technical University, St. Petersburg. E-mail: sergiiblack@gmail.com