

Workflow towards autonomous and semi-automized UXO Survey and Detection

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Session Summary: Underwater Unexploded Ordnance (UXO) Detection and Remediation

Workflow towards autonomous and semi-automized UXO Survey and Detection

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This paper presents a workflow for UXO detection based on multibeam data in combination with AUV-based ground truth. An artificial neuronal network (ANN) is trained on manually annotated multibeam data and aims for making UXO detection and the generation of target lists faster and more objective. Prior to annotation the data is checked according to several quality factors to ensure that it fits for the purpose of object detection. The quality and accuracy of annotations has an influence on the predicted probabilities of the ANN, as the probabilities of the annotations determined by the experts are considered during training.

To make this whole workflow even more effective in terms of survey time, the quality check and ANN analysis can run automated on the survey vessel. While MBES mapping continues, autonomous underwater vehicles (AUVs) can be used to ground truth possible targets with additional sensors, such as geomagnetic and under water cameras. The more precise the training data, the more reliable the ANN outcome will be.

INTRODUCTION

Munitions in the sea present a global issue with effect on both maritime economy and marine environment. Due to military actions during wars, post-war dumping, and military test- and training activities, large amounts of unexploded ordnances (UXO) and discarded munition material (DMM) rest on seafloors worldwide. With an increase in offshore development, such as windfarm installations, the topic gained increasing public and political attention over the past ten years. Offshore construction projects are not only delayed due to extensive munition detection surveys, but also face high costs for explosive ordnance disposal (EOD). UXO surveys are typically performed by qualified survey companies, which are contracted by offshore developers, e.g., energy companies. The Quality Guideline for Offshore Explosive Ordnance Disposal EOD (Frey et al., 2020) gives a summary about suitable survey methods and describes how to meet the generally accepted engineering practice. It subdivides the EOD process into four phases: Phase I describes the preliminary survey, including research about the target area in terms of its military history and natural site conditions. The technical survey is phase II and consists of data acquisition, processing, and interpretation of the area of interest with the aim of identifying potential munition objects in geophysical and hydroacoustic data. Resulting target points are then further investigated in phase III. In case target objects can be verified as munitions, they are investigated in greater detail and subsequently cleared and disposed of (phase IV). This process chain is time-consuming and the EU-funded project BASTA (Boost Applied munition detection through Smart data inTegration and AI workflows) aims at developing workflows that allow instantly generating target lists and simultaneously surveying the area of interest and target points. This can be achieved by the use of autonomous underwater vehicles (AUVs) in combination with data interpretation algorithms based on artificial intelligence (AI).

State-of-the-art methods for munition objects localization are towed magnetometers, side-scan sonars (SSS) and synthetic aperture sonars (SAS), whereby the latter is mainly used by the military. The sonar systems produce high-resolution acoustic images of the seafloor and surficial objects but, since they are usually towed, can suffer from positioning inaccuracy due to errors of ultra-short baseline (USBL) underwater positioning systems. Complex post-processing is then required to enhance the positioning accuracy (Stutter et al., 2008). Magnetometers can detect both proud and buried magnetic objects.

Within the BASTA project, spatial mapping is performed via high-resolution multibeam echosounder (MBES). To ensure sufficient data quality, MBES data are checked, according to specific data quality factors, which determine, whether the dataset is suitable for detecting UXO of a specific size. Subsequently, the data are annotated by experts and target points are ground truthed via AUV-based photo mosaics and magnetic data.

To generate a contact list, MBES data can be annotated either by experts or by using a trained artificial neural network (ANN). The aim is to automate as many processes as possible and to save surveying time by running processes in parallel that were previously conducted in sequence. With a well-trained ANN it will be possible to annotate MBES data immediately following their acquisition. Ground truthing can be automated most easily by using AUVs. Equipped with a camera and magnetic gradiometer system, several AUVs can operate simultaneously and independently to map possible targets, while MBES mapping of the larger area continues. The following section describes what is required for setting up an ANN and how such an autonomous and semi-automated UXO survey can be designed. Subsequently a study from the German munition dumpsite Kolberger Heide in Kiel Bay, Baltic Sea is presented.

All methods presented here were applied in Kolberger Heide, which is a marine munitions dumpsite in German coastal waters with water depths ranging from 8-20 m. It was established as a munitions dumpsite after WWII by order of the British military forces. Two official dumping grounds (0.5 and 1 km²) are located within an area of 15 km², in which UXO and dumped munition must be expected. According to historic records, an estimated 1,600 t of munitions (combination of mines, depth charges, grenades, and artillery munitions among other)

(Kampmeier et al., 2020) are assumed to be present here. The object sizes range from 7 m length (torpedoes) over 2.5 m length (ground mines) and 1 m length (depth charges) to less than 0.5 m for grenades and artillery munitions. The sediment is very heterogeneous and characterized by fine to medium sand and stony patches.

METHODS

A. WORKFLOW

In order to reliably detect and identify munitions in the sea, surveyors follow workflows that have been developing and evolving in past years. Relevant publications comprehensively describing technical surveys with the aim of detecting munition include inter alia the Quality Guideline for Offshore Explosive Ordnance Disposal (Frey, 2020), the CIRIA guideline Assessment and management of unexploded ordnance (UXO) risk in the marine environment (Cooper and Cooke, 2015) and the Guidance for geophysical surveying for UXO and boulders supporting cable installation (OWA, 2020). However, these documents either consider the survey of a large area of interest and the detailed investigation of a potential munition target point as two distinct processes (Cooper and Cooke, 2015; Frey, 2020) or do not describe the target point investigation at all (OWA, 2020).

In areas other than dedicated munition dump sites, over 90 % of target points regularly turn out to be objects that are not munition but other anthropogenic objects such as metal plates and wires or boulders (Guldin, 2020). This is true even though a survey is commonly conducted with SSS, magnetics and MBES acquiring data in parallel. Due to the large number of false positives, target point investigation is a cost driver in offshore EOD. Improving the capacity to reduce the number of false positive target points and integrating the technical survey of the area of interest with the detailed investigation of points of interest would therefore be beneficial. In order to achieve these aims, the following abilities were identified:

- The ability to immediately perform an objective data quality check of all acquired survey data (Ability I).
- The ability to automatically generate preliminary target lists aboard the survey vessel (Ability II).
- The ability to automatically run target point investigation without requiring the vessel to interrupt the survey (Ability III).

Given the absence of industry wide availability of these competencies, it can be noted that the distinction and separation of technical survey and target point investigation in the previously mentioned guidelines are a result of technical limitations at the time of their publication.

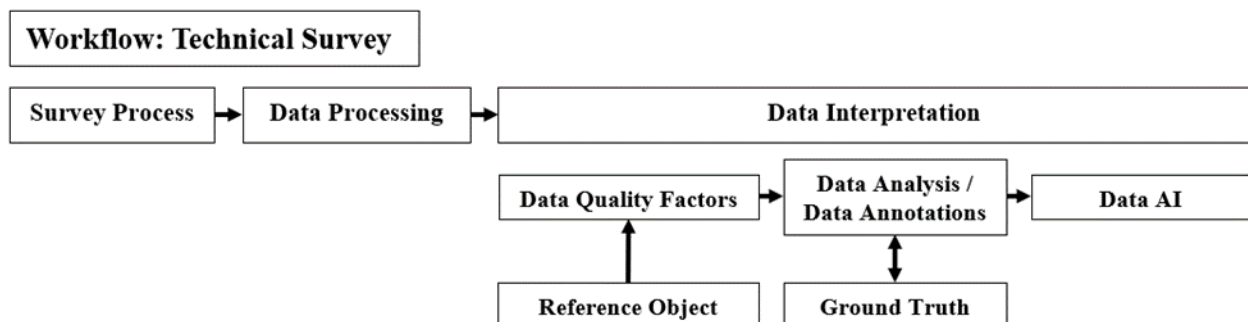


Figure 1: Workflow for technical surveys with the aim of detecting and identifying munition in the sea.

Figure 1 shows the workflow that is used to acquire data in Kolberger Heide. It has the potential to provide the abilities mentioned above. Prior to the workflow the surveyor needs to be aware of the survey requirements in order to design the survey in such a fashion that a defined reference object can be found. Once this preparatory step is completed the survey process (i.e. the data acquisition) can start. As data are recorded both automated and human data processing takes place on the vessel. Subsequently, the process of data interpretation begins. First, all data must pass a data quality check. Data quality requirements depend on the reference object and the natural conditions of the area (ability I). Once the data have passed the quality gate one or more EOD experts manually annotate them to determine where target points with potential munition objects are located. The target points are then investigated by AUVs that are equipped with magnetometers and cameras to either confirm or to reject the presence of munitions (ability III). The newly acquired information can then be used to train the ANN and provide an improved target list in the future. With a fully trained ANN, the step of data annotation can be partially automated and is therefore less prone to human error (ability II). The following sections describe the individual steps of this workflow in further detail.

B. SURVEY PROCESS AND DATA PROCESSING

MBES is widely used for hydroacoustic surveys to monitor water depths and underwater obstacles in marine traffic routes. So far, it is less relevant for UXO surveys because high data resolution is critical for the recognition of individual objects. MBES resolution is limited by range (i.e. the distance between the transducer and the seafloor) and hardware-related parameters, such as beam opening angle, acoustic frequency and ping rate. Whereas large munition objects (> 1 m) can be well displayed in shallow waters (10-20 m) as demonstrated by Kampmeier et al. (2020), smaller munitions like grenades have dimensions that are similar to or smaller than beam footprint sizes. This leads to fewer pings per object and less distinct shape information, which are essential for object detection and even more for identification. Since for offshore construction purposes, the detection of large UXO is most relevant, high-resolution MBES data constitute a further state-of-the-art method. An additional benefit of ship installed MBES systems is the high positioning accuracy for each sounding. Morphological derivatives, which can be calculated from the bathymetry, enhance target visibility. Additionally, most modern MBES are capable of recording backscatter time series data (snippets) which provide additional information about seafloor properties and surficial objects, similar to side-scan sonar (Kunde et al., 2018).

The data set presented here was acquired in 2018 with a mobile RESON T50-P MBES. Since water depth in Kolberger Heide is about 12 m and the MBES has a beam opening angles of $0.5^\circ \times 1^\circ$, a raster resolution of 25 cm was achieved. Beam footprint sizes are around $0.02 \text{ m} \times 0.17 \text{ m}$ for nadir beams in 10 m water depth. The survey was conducted with 120° swath angle. Navigation was enhanced by using an online RTK service and data were processed with the software QIMERA (QPS), which was used for calibration, sound velocity correction and point cleaning. After the data quality check but before the start of the annotation, data were exported as 25 cm raster for annotation and contact list generation.

C. DATA QUALITY FACTORS

Data quality factors can be used to check whether the acquired data set is fit for the purpose of detecting a specified reference object. The reference object is determined prior to the survey and constitutes the smallest object that needs to be detectable by the employed survey methods. Threshold values for data quality factors are calculated on the basis of different reference object properties. Acquired data can then be compared to this threshold value, to determine whether they can be used to detect the reference object. If the data quality factors indicate that it is unlikely or even impossible to detect the reference object in the data (i.e. the data do not meet the threshold values), either additional survey needs to be conducted or – if EOD risk assessment permits it – the reference object needs to be changed. Both of these management options may also be applicable for subsections of the area of interest, either if data quality is only insufficient in part of the survey area or if a change of the reference object is only permissible in limited spaces. Accordingly, subsequent steps such as data analysis and annotation should not take place unless data have been found to be of sufficient quality.

In the BASTA project, data quality factors were defined by reviewing existing literature. Subsequently stakeholders, who are conducting professional technical surveys that are part of EOD campaigns, sensor producers and scientists working in the field, were confronted with the data quality factors. Stakeholder feedback was

gathered by means of a questionnaire and four intermediate remote workshops. A final on-site workshop is pending and thus evaluation of the final results is still in progress. At the time of submission of this paper, the following seven quality factors were already approved by stakeholders:

- Data point spacing (along track and across track)
- Beam footprint (along track)
- Beam footprint (across track)
- Coverage
- Horizontal positioning accuracy (of the footprint)
- Vertical positioning accuracy (of the footprint)
- Acoustic center frequency

It is possible to execute the quality check with the seven approved factors listed above. As is evident from the fact that numerous data quality factors refer to individual beams, the data quality check for multibeam data needs to be performed on point data and not on raster data, as too much information is lost during gridding.

D. DATA ANALYSIS AND ANNOTATIONS

For the purpose of target list generation and setting up an ANN, a training data set with annotations is needed. For this study, an area of 560 x 500 m was chosen for annotation by six different experts. The MBES raster of this area has a resolution of 25 cm, which allows safe identification of larger munition objects, as predicted by the quality factors. The fewer pixels an object is visualized by, the higher the uncertainty. Morphological derivatives, such as slope, curvature, hill shade and Topographic Positioning Index (TPI) calculated on the bathymetry, can enhance identification capabilities. Other identification parameters are patterns or clusters and the geological context. Dumping often took place, while a vessel was steaming, producing tracks of single objects at similar distances to each other on the seafloor (en-route dumping). Furthermore, single objects, or piles of objects in a rather homogeneous environment might be an indicator for artificial items. On the other hand, it is difficult to differentiate munitions from rocks and boulders. MBES backscatter snippets can add information on seafloor properties and support UXO detection. However, since the ANN was developed to perform on MBES bathymetry data, it was not yet included. The raster was loaded into a QGIS project and each expert marked munition objects with a polygon shape file. The probability of each polygon being UXO was assigned in percentages. All six annotations and probability datasets were then merged into one shape file.

E. GROUND TRUTH

Two GIRONA 500 AUVs, owned by GEOMAR, were used for ground truthing via underwater camera and geomagnetic measurements. The characteristic of the Girona 500 is its capability to go at very low speed and to be individually reconfigured for different tasks.

As optional payload a CoraMo mk II Camera, which is developed by the GEOMAR AUV team, is mounted on both vehicles. This downward or forward-oriented camera system for photographic surveys can take up to two images per second with a resolution of 12.34 MP, which allows the generation of high-resolution photo mosaics of the seafloor.

The operation of AUVs can generally assist in improving the precision and reliability of the acquired magnetic data. The utilized magnetic sensors are FGM3D/100 UW II 3-axis fluxgate magnetometers from SENSYS GmbH. During the first phase of the BASTA project, GEOMAR constructed a basic modular system consisting of aluminium poles and submersible magnetometers that can be attached to GEOMAR's Girona 500 AUVs at a lateral distance of 2 m to the front of the AUV (Figure 2). Each magnetometer is sampling three spatial components at rate of 200 Hz. The magnetometer component consists of two sensors forming a gradiometer in a vertical distance of 0.5 m.

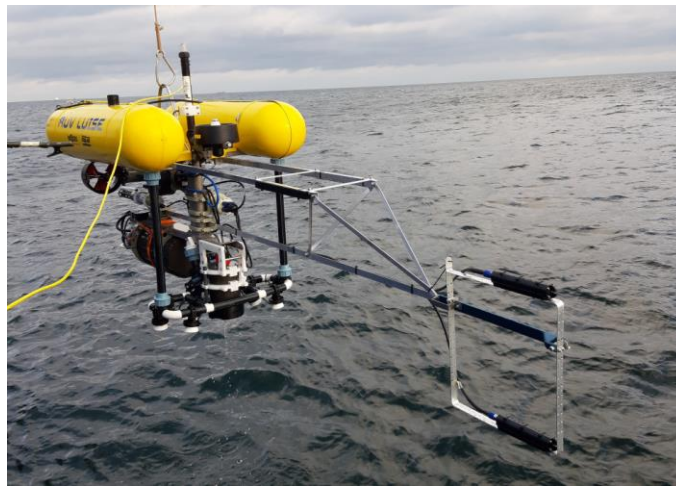


Figure 2: The vertical magnetic gradiometer mounted to GEOMAR's AUV LUISE.

F. DATA AI

An ANN can annotate the distinct shapes of UXO objects on the seafloor in the MBES data. This is facilitated by using convolutional layers in the network. Different types of UXO objects can be distinguished by an ANN, given the right training data. As ANNs rely on the principle of learning from data, a good training dataset is crucial for their performance. The annotation has to be both complete and accurate to get good results from an ANN. The goal is to highlight possible UXO objects in the MBES raster data. For this objective the authors rely on semantic segmentation, a common task in deep learning. The task is to assign a probability to each pixel of the input to classify it as UXO or no UXO. One advantage of this approach is the use of not only the pixel information itself, but also the information of the surrounding pixels. This leads to regularization and smoother results.

The U-Net model architecture for the ANN was introduced in Ronneberger et al. (2015). A U-Net uses a compression of the data from input dimension to a lower resolution in multiple halving steps followed by an equal number of expansion steps of the dimension by factor two. Additionally, the information of steps with similar dimension is passed forward. The main building blocks of the model are convolutional layers. These layers have the advantage of generalizing feature information from one location in the input and make them applicable across the entire input. This architecture was used on various types of data apart from the medical application outlined in the original paper, e.g., finding the road in images (Zhang, Qingjie, and Yunhong, 2018) or discriminating forest types from remote sensing data (Wagner et al., 2019).

The model uses the bathymetric map as input data. Approaches including not only the bathymetry, but also the backscatter from the multibeam echosounder or magnetic data are also possible. To train the data expert annotations are used. These come as a shape files, which are converted to a raster file. The annotations include the probabilities indicating the certainties of the annotators whether an object is UXO or not. No distinctions are made between different UXO types. Therefore, the model creates a binary output, the probability of a pixel to be UXO.

The training process for the given dataset is not straightforward. Due to the small size of the dataset, it is necessary to make extensive use of augmentation techniques. The top-down perspective of the data allows for the use of rotation and mirroring of the data. Additionally, scaling of the data by small magnitude is possible as well. However, due to the low resolution of the data, it is not advised as the results would be created using interpolation techniques which flatten the data. The augmentation is done on the fly during model training.

The training of the aforementioned models can be done on common CPUs within about an hour. To monitor the progress of the training the dataset is split into a training and a validation set. The performance on the validation set is used to decide when to stop training the model. The loss function accounts for the imbalance in UXO vs. non-UXO areas of the test area by incorporation an adjustment factor. Additionally, an improvement in performance after including the percentages of the annotations in the loss function was evident. The number of false positives dropped significantly.

RESULTS

A. DATA QUALITY FACTORS

Figure 3 provides an example of two data quality factors that were applied to two different reference objects. On the left a subsection, the test site, of Kolberger Heide is shown. It should be noted that the area is deepest in the northeast corner (blue) and that the water depth is decreasing towards the west and southwest (red). On the right side, the four graphs, show the same area, but with data quality factors applied to each beam represented by a colored point. Data quality is measured relative to the threshold values indicated in the figure caption. A value of 1 (yellow) shows that the beam meets exactly the threshold value of that data quality factor. The more the color changes towards green (value of 2), the more the data point outperforms the data quality requirements. The more the color changes towards red (value of 0), the less sufficient the data quality of that beam.

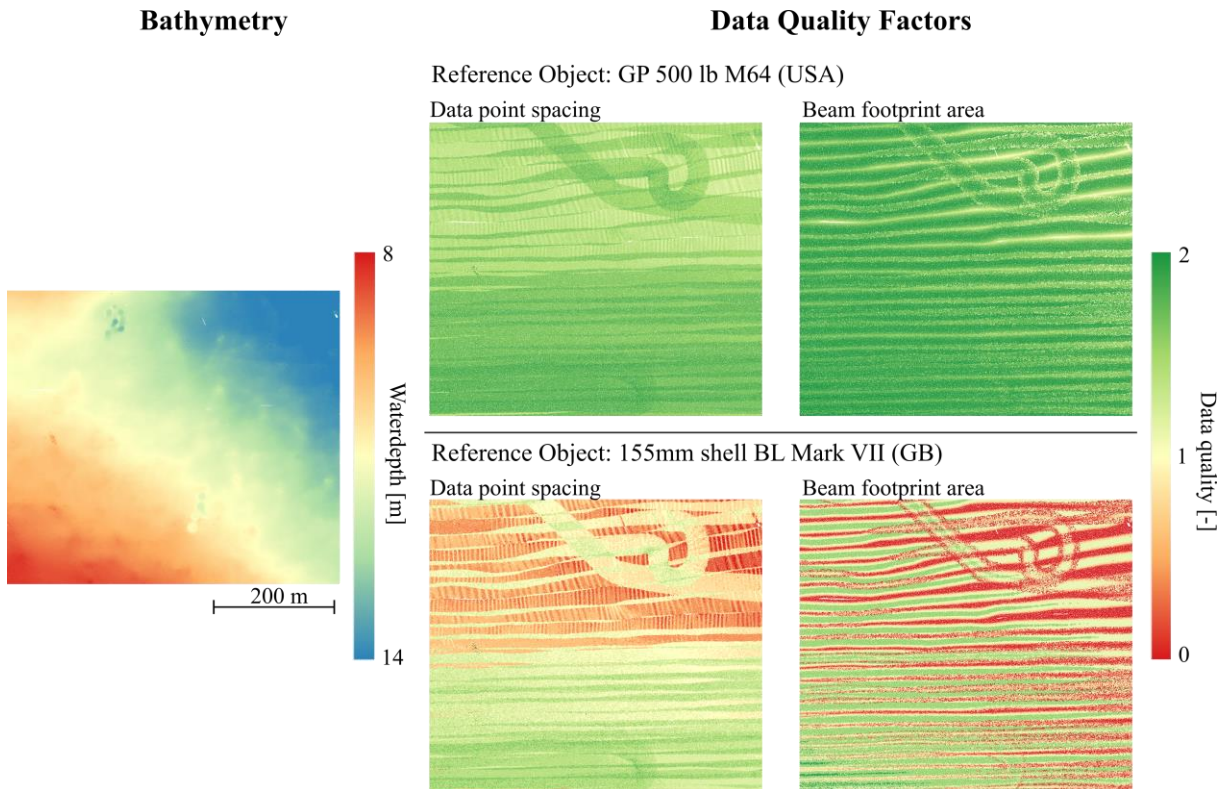


Figure 3: Bathymetry measured with the MBES in the test area (left) and exemplary data quality factors (Data point spacing D , Beam footprint area F – combination of beam footprint along track and across track) for two different reference objects (right). The data quality factors are computed relative to the smallest dimension d_1 of the reference object as Data point spacing: $((d_1/3)/D)$ and Beam footprint area: (d_1^2/F) .

Placing thousands of colored points (i.e. beams) next to each other leads to the generation of the striped patterns visible in the figure, which follow the survey lanes taken during data acquisition. The upper row on the right shows the quality factors data point spacing and beam footprint area, which combines the beam footprint along and across track for a U.S. American general-purpose (GP) 500 lbs (pound) M64 bomb. Both data quality factors are conditional to the shortest dimension of the reference object (d_1). The threshold value of data point spacing is defined as one third of the shortest dimension of the reference object. That means that the minimum distance between two beams must not be further than $d_1/3$. The threshold value for the footprint area cannot be larger than the shortest dimension of the reference object squared. The optimal threshold values are still investigated and are not finally defined at this stage. From the two graphs it is evident that the majority of beams surpass the data quality requirements and thus pass the data quality check. The acquired data approach the threshold values in greater water depths as both footprint size and data point spacing increase with the distance between the transducer and the seafloor. The picture looks different for the lower row, which tests the same data quality factors for a British 155 mm artillery shell BL Mark VII. As this type of munition is smaller than the American general-purpose bomb, it is more challenging to detect. For data point spacing, the graph shows significantly more red points in the northern half of the area, which may be due to less overlap between survey lines. An additional survey on the area with the same system setup could resolve this issue. For the beam footprint area, the outer part of the multibeam swaths and the deeper section in the northeast result in quality values below 1 and thus red areas on the map. In this case it would be possible to decrease survey line spacing and only use the central part of the multibeam swath. On the other hand, it demonstrates a limitation of hull based multibeam mapping. AUV-based mapping could get the system closer to the seafloor, thereby avoiding beam footprints that are too large for munition objects of this size.

B. DATA ANNOTATIONS AND ANALYSIS

In total, 1281 objects have been manually identified based on the gridded MBES data and reveal spread munitions all over the annotated subsection in Kolberger Heide. As predicted by the quality factors, objects of sizes less than 1 m can be hardly identified on a 25 cm resolution bathymetry raster and therefore, small suspicious points are assigned with only low probabilities. A more detailed specification of munition type is only possible if the pixel number is high enough to discriminate certain shape characteristics. That's why ground mines and torpedoes got highest probabilities. Expert consensus differs widely and only in 5 % of the annotations, all experts agreed on an object (Figure 4). The main annotations represent objects, which were annotated by only one expert.

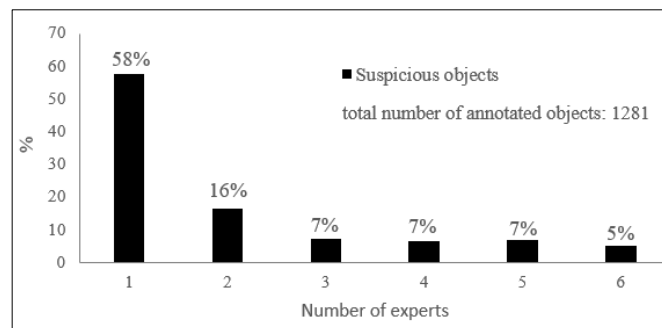


Figure 4: Amount of identified UXO in relation to the number of experts (max. 6), who agreed on identification.

This fact makes it important to weight the input data for ANN training regarding number of experts and probability. Nevertheless, distinct distribution patterns of objects can support the decision process. In Figure 5 (1a and 1b) a track of the munitions is shown, caused by en-route-dumping while the vessel was steaming. It is characterized by several objects of same size in regular distance to each other. In between, smaller objects do occur. Looking onto the objects independently, none of them could be identified as UXO with high probability. But the regular pattern emphasizes an artificial origin and cannot be explained by seafloor geology.

C. DATA AI

The ANN outputs a raster with predicted probabilities from 0 to 100 %. On a first view, the predicted UXO distribution resembles the expert annotations (Figure 5; I a and I b). The bigger round objects, which are part of an en-route-dumping track were predicted by the ANN with high probabilities. The smaller objects in between were also discovered, but only with low certainty values. In II b of Figure 5, even more objects were predicted, than annotated by experts. Magnetic ground truth data of a sub area indicate high amplitudes for two annotated objects, for which the algorithm gave only low probabilities. Small items in the vicinity do not show any magnetic signature, which clearly counteracts the expert annotations and ANN predictions.

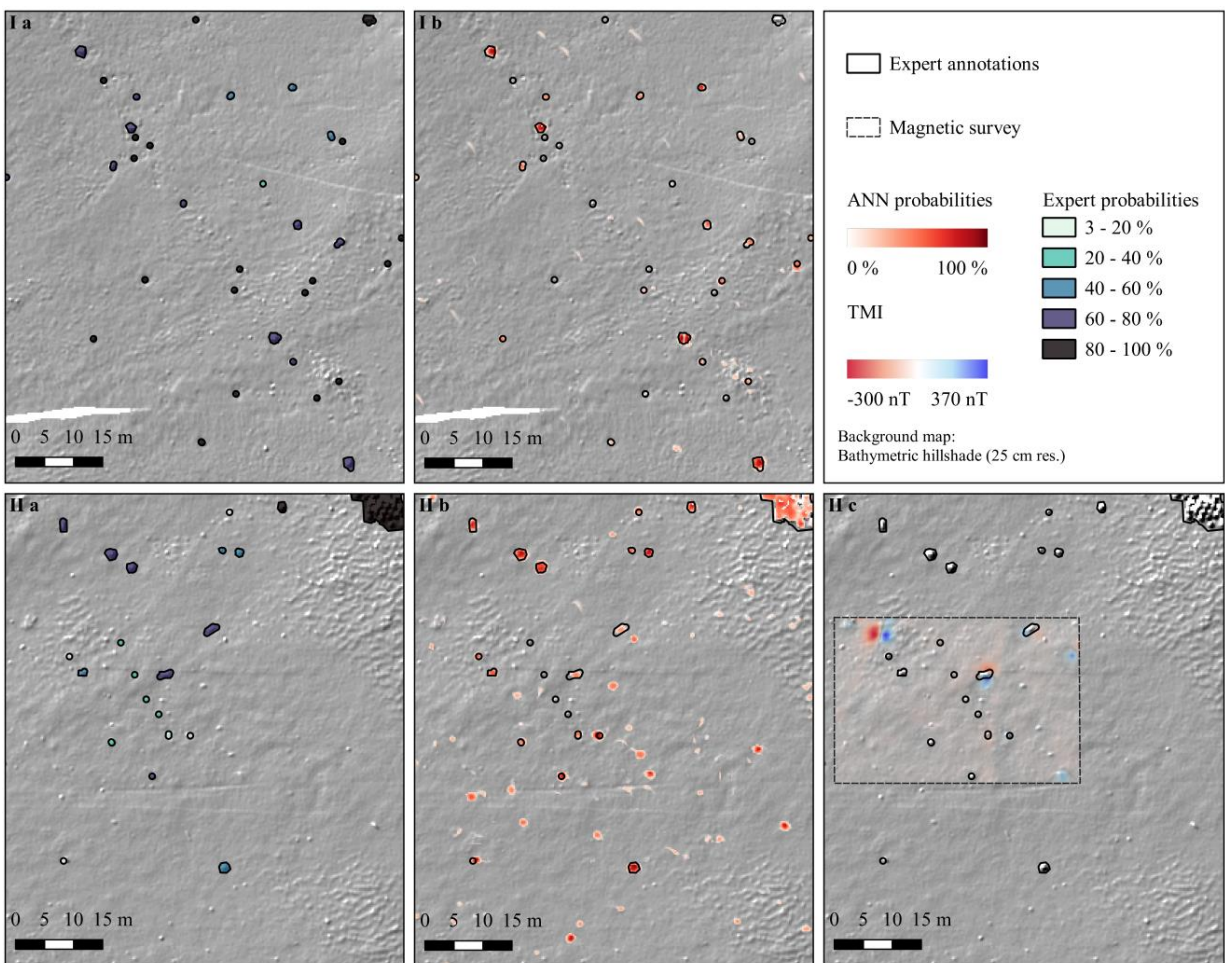


Figure 5: The maps show in greyscale the bathymetric hillshade of the seafloor of the dumpsite Kolberger Heide. Objects have been annotated by experts with certain probabilities (I a and II b). In I b and II b, the probabilities generated by the ANN are shown. A magnetic AUV survey reveals that several annotated objects are most likely no UXO (II c).

Comparing both data sets, 20 % more objects were predicted by the ANN than annotated by the experts and based on the expert annotation, the sensitivity range of the ANN is 0.81. This means that the ANN is able to identify 81 % of the annotated objects. Since expert annotations are not fully ground truthed yet, this number only reveals the ANN capability to work with MBES data. Reliable true and false positive and true and false negative analysis of real UXO detection performance, will be only possible after further ground truth data were obtained.

D. GROUND TRUTH

Only a small number of the sub-area has been ground truthed so far. Further ground truth data are either not fully processed and analyzed yet, or planned for up-coming cruises. Figure 5 (II c) shows the interpolated total magnetic intensity (TMI) anomaly field of a 40 x 30 m² AUV mission area at the Kolberger Heide. The altitude of the mounted magnetometers was 1.2 m above the seafloor and the AUV moved at a velocity of 0.4 m/s. The AUV mission tracks were east-west oriented and the average line spacing of the sensor tracks was 0.5 m. The 2D interpolation of the TMI data was performed using a linear radial basis function (RBF) interpolation. The figure shows numerous magnetic anomalies, some producing huge amplitudes of hundreds of nT, smaller anomalies produce only low amplitudes of a few nT to several tens of nT. Two north-south oriented magnetic signals can be observed, one in the very left part and another one in the central right part of the image.

CONCLUSION

With this exemplary study, a workflow for autonomous and semi-automated UXO detection was tested. Once it is fully established, it will allow the detection of possible UXO and the generation of target lists (phase II and phase III) in less time. Instead of time-consuming manual data annotation, target list generation can then be done by using a trained ANN. Nevertheless, the outcome of this study clearly emphasizes the need of a high-quality training set for setting up the algorithm. Artificial intelligence algorithms are widely applied onto subsea data for seafloor classification and habitat mapping (Marsh & Brown, 2009). Compared to spatial classification, the challenge in UXO detection on MBES data is the reduce cell number per class. Within the SERDP project SAS data is used for automated UXO classification and shows promising results in discrimination of different munitions types (Lim, 2015). Unfortunately the processing of SAS is complex and SAS system are still not a standard method in EOD operations.

Purely based on MBES data, the annotation is highly subjective and high probabilities can only be assured for objects of a certain size and shape or within clear dumping patterns (e.g. en-route-dumping track). Checking the data quality before the actual manual annotation can help to assign more precise probabilities. If the data is not suitable for UXO detection of a certain size, this needs to be considered. To improve the quality of training data and to verify manual annotations, ground truth is essential. Here, the annotation was mainly done without ground truth, which was performed on a later survey and only used for checking the ANN performance. Especially low-probability objects should be re-surveyed with additional sensors (e.g. geomagnetic or camera). Despite limited resolution, MBES data are useful for fast area mapping and allow straight forward automated analyses with subsequent target list generation via artificial intelligence.

The next step will be to generate and analyze more AUV based camera and geomagnetic data to improve manual annotations for the training set. Once this is accomplished and the algorithm is well trained, it can be directly applied to new data sets. Additional ground truth will then be needed for fine-tuning, but the task of manual annotation will decrease significantly. For better accuracy, more sensor data shall be incorporated into the ANN, to enable direct analysis of ground truth data, like camera images and geomagnetic data. With adequate training data, it will be possible to adjust the ANN for not only detection, but also for UXO classification. AUVs provide the perfect solution to effectively reduce survey time. They could also be modified to run algorithms online on measured data and to change their survey patterns accordingly. This will make UXO surveys much faster and more subjective than today.

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