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PARAMETRIC CLASSIFICATION OF FERROMAGNETIC BOTTOM OBJECTS BASED ON AN IMAGE ANALYSIS OF MAGNETIC ANOMALY MAP

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ABSTRACT

The magnetic properties of ferromagnetic objects or naturally occurring minerals such as ores can be detected and mapped using magnetic field theory studies. Magnetometry water area survey are commonly used for the purposes of detecting the oil or gas pipelines, shipwrecks and their equipment (i.e. anchors or engines), wrecks of airplanes or cars, barrels, containers, unexploded ordnances and mines and other metal debris. It is possible by detecting the magnetic anomalies they induce.

The following article is presenting the stages of geoclassification of the bottom objects based on the analysis of a magnetic anomaly map. In order to determine the conditions and parameters of geoclassification, a catalog of ferrous seabed bottom features was previously developed. The catalog is dedicated to inland water areas and contains the characteristics of features potentially possible to meet in these waters along with the parameters of the magnetic anomaly they induce: e.g. spatial dimensions (length, width, area, perimeter, value ratio) together with the value of the generated anomaly itself. The further part of the article presents the map segmentation process, carried out for the purpose of detecting the areas covered by an anomaly and then dimensioning it along with the classification procedure. The whole process is summarized with the verification of the correctness of the method's operation on modeled and real anomalies.

Keywords - magnetic anomaly, ferromagnetic objects, image analysis, classification

1. INTRODUCTION

The magnetic method is based on the measurement of the magnetic field strength. Changes in the value of the magnetic field indicate a change in the magnetic properties in the studied local geological center, thanks to which it is possible to detect and determine, among others, ferromagnetic bottom objects. Magnetometry is used in regional issues, such as the recognition of igneous structures or dedicated geological layers, as well as in local cases, such as the detection of unexploded ordnance, shipwrecks (Mattei et all, 2015, Dimitriu 2019,, Dimitriu et. al. 2019, Dimitriu et. al. 2021) or pipelines. Magnetometric measurement is also widely used in archaeological searching, e.g. for the determination of barrows or other archaeological structures (Monteiro & Costa, 2019). Magnetometry is not limited to land or sea measurements. Currently, many unmanned flying systems are equipped with this type of sensors. So are the satellites. This gives an unlimited surveying possibilities. After processing the raw data, on the basis of the data recorded with the magnetometer, final products are developed in the form of numerical land cover maps, contour maps containing isogonal distribution, as well as 3D maps and a point list of detected objects. However, the interpretation of the data itself is not so obvious and requires, above all, extensive geophysical experience, often supported by appropriate dedicated software or specially for this purpose modules based on signal analysis (Underhay 2021, Kolster

2021, Ibraheem i in. 2021). Analyzing the literature, information was also found on the classification of magnetometric data based on the use of the Library Matching tool integrated with the UX-Analyze software (Kantsios, 2013, Kantsios et. Al. 2013, Kantsios et. Al. 2012). The tool carries out the process of data classification (clustering) based on the so-called information libraries with user-defined object classes. Following this solution, the authors have developed a catalog of objects, which at a later stage is a tool supporting the classification, in the form of an information library.

The current development of digital imaging techniques allows for a fairly common application of recognition algorithms to various areas of life and the economy. The range of possibilities of using image recognition is extremely wide, ranging from medicine, through national defense and security, to the control of wear of systems or components in machines. Monitoring systems are widely known, with the help of which systems are able to identify a specific car by a license plate, indicate a specific person in a photo or identify it with the help of an iris or fingerprints. In the process of recognizing the content of an image, there are two stages of operation: object detection and its identification. In the first stage, with the help of algorithms indicating the edges of objects or its outline, the area of the image is assessed: the dimension along with the shape. The operation of the second stage is based on machine learning or more and more common artificial neural networks. Both methods give a good results in the case of e.g. landscapes, crop control (Pearline, Kumar 2022), photos of traffic or photos of people and still life (Xiang et al. 2020; Dharini, Jain 2021, Sadgrove et al. 2018, Mani et al. 2022, Zhao et al. 2022). In the case of images acquired by remote sensing methods, such as sonar imagery, satellite images related to land cover, or just maps of magnetic anomalies, the effectiveness of detecting small objects decrease. This is mainly related to the resolution of the analyzed images. In order to improve the quality of learning of neural networks dedicated to such images, and thus strengthen the network's potential to detect small objects in images, e.g. cascade object detection techniques or hierarchical segmentation methods are used (Shivappriya et al. 2021).

Another method of recognizing images is fuzzy logic. It was initiated by Letfi Zadeh and is directly related to the fuzzy sets theory. In the method of recognizing objects in an image using fuzzy logic, between the state of assignment to a specific class, there are ranges of intermediate values that determine the degree of belonging of a given identified object to specific categories of classes (Tang et al. 2020, Choy et al. 2020).

All the methods described above require a large number of input data for the purpose of determining correctness in class intervals. In the case of not having a sufficiently large data set, it is possible to try to define the classification using the parametric method, setting certain conditions for belonging to a given class.

The analysis of the literature revealed several publications concerning strictly the classification of objects on the basis of magnetic anomaly maps. Information on this subject can be found, inter alia, in the following studies: Nazlibilek et. al. 2013, Pregesbauer et. al. 2013 or Khodayari-Rostamabad et. al. 2009. The first refers to mine and unexploded ordnance (further UXO) detection and the classification is based on previously defined dimensions of potential objects. The second one refers to UXO also, but the classification is based on anomaly values and assigning the read value to predefined limits. The last one mentioned above refers to pipeline leakage classification. In order to define the pattern catalog, the anomaly inverse modeling method was used, for which the radial artificial neural network (RBFN) was used.

The main goal behind the development of the proposed parameteric geoclassificatoin metod was to catalog the ferrous objects and its parameters. For that purpose obtaining necessary data or information on confirmed or verified anomalies was needed. While developing the catalog of objects, a number of large-scale consultations with institutions dealing with broadly understood geophysics, foundations, universities, commercial and R&D companies dealing with this type of measurements, both domestic and foreign, were carried out. A certain amount of data was obtained from the Maritime Office in Szczecin, carried out on the Szczecin-Świnoujście fairway, during the tests of the cleanliness of the fairway before the dredging, and some data from measurements at the LNG port. The data recorded on the fairway are practically unsuitable for research purposes, due to the fact that they are extremely disturbed by the port infrastructure. Data on UXO was obtained thanks to cooperation with Stanisław Kuzmanow from Explosive S.C., based in Gdańsk Data referred to Puck harobour survey campaign, Poland. Data on wrecks were obtained thanks to cooperation with Dr. Radu G. Dimitriu, the Head of Gravity & Magnetics, The National Institute for Marine Geology and Geoecology - GeoEcoMar, Bucharest, Romania. These data are refered to Danube river, at Prahovo . Data on anchores were obtained thanks to cooperation with Steve Sullivan, geophysicist and sea surveyor. Data refered to Ventura, California, USA.

Initially directory categories of bottom objects was assumed: shipwreck, anchor, UXO, pipeline and others. That is, objects that can potentially be found in the water area of Odra river aquatorium. During the data acquisition and collecting process, it was not possible to get enough data for the pipeline category. Therefore, this class was omitted in further analyzes.

The further part of the article describes the procedure of segmentation of the magnetic anomaly map image along with the detection of the areas occupied by the anomalies and their dimensions, the developed catalog of objects, the conditions defining the classification parameters and the result of verification of the correctness of the method.

2. IMAGE ANALYSIS OF MAGNETIC ANOMALY MAP

Magnetic anomaly map image analysis includes segmentation processes to obtain the specific information about the objects that they present. Segmentation methods can be classified into classes according to the type of information that is used in the segmentation process (Pratt 2014):

- point methods,
- thresholding - e.g. by selecting a threshold based on the image histogram, the result is obtaining a binary image,
- clustering - creating areas based on the features assigned to pixels as a result of applying clustering (grouping) algorithms,
- edge detection methods - the use of this type of methods requires the use of one of the edge detection algorithms,
- area methods, which include:
  - region growing,
  - region merging,
  - region splitting,
  - split & merge,
  - watershed segmentation,
- hybrid methods - using two or more of the above methods, e.g. area growth with the use of information about the edge course.

Magnetic anomaly map images are not images that can be easily interpreted by computer systems. There are no clear, cut-off edges of individual elements of the picture, as is in the case, for example, in the picture of a house or a group of people. Due to the fact that the image of a magnetic anomaly is not easy to interpret from a computer point of view, the described method of geoclassification uses a hybrid method that combines:

- thresholding,
- edge detection methods and

- area methods.

All analysis of the magnetic anomaly map images were carried out in Matlab software. Based on the knowledge obtained during the analysis of various image segmentation methods (Bodus-Olkowska, Uriasz 2019, Bodus-Olkowska, Uriasz 2020), several methods were selected and parameterized and arranged in the appropriate order of operation. Thanks to this, a hybrid method of segmentation was created, suitable for the analysis of both The scheme of the hierarchy of operations is presented in a diagram below (Fig. 1):

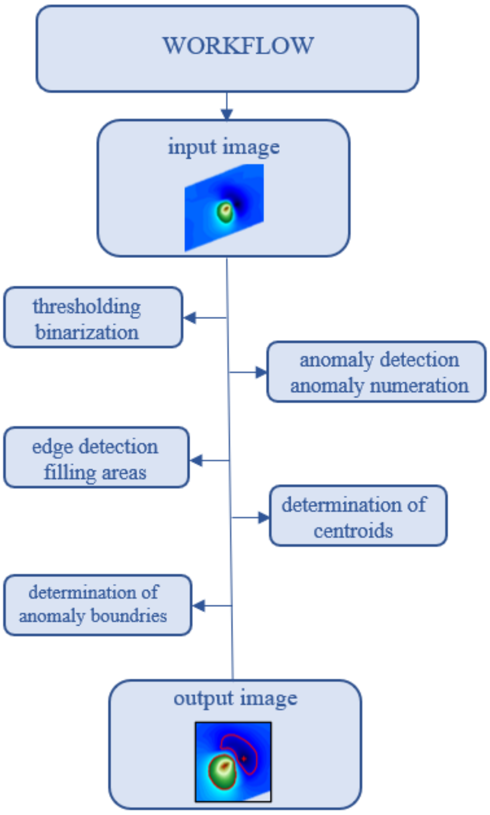

Fig. 1. Workflow of the image segmentation in proposed parametric method (source: own study).

The major goal of the first step of segmentation is to keep only the areas occupied by the magnetic anomaly in the analyzed image. In this purpose the thresholding and then binarization is carried out. The result of this step is presented on a figure below (Fig. 2).

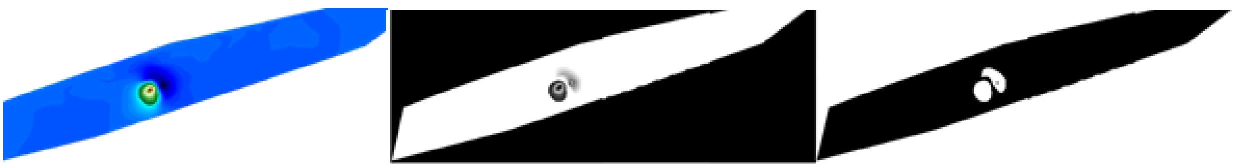

Fig. 2. Image thresholding and binarization (source: own study).

The next step of image segmentation implemented in the method is the detection of areas occupied by the anomaly separately for positive and negative values and their numbering. For this purpose, the bwlabel and regionprops functions were used in the developed script. The sequent step is to detect the edges of objects presented in the image. The following methods were programmed for this purpose: Canny, Prewitt, Sobel and Roberts. Then close the edges and fill the surface again.

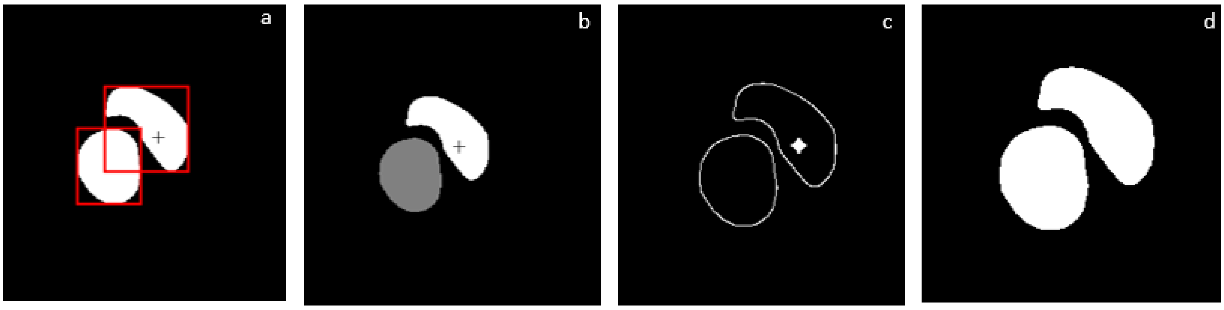

Fig. 3. Anomaly areas detection, numbering, edge detection and filling the areas of detected anomaly (source: own study).

The last steps in the map image analysis are the determination of centroids for each anomaly area and marking its boundaries on the analyzed image.

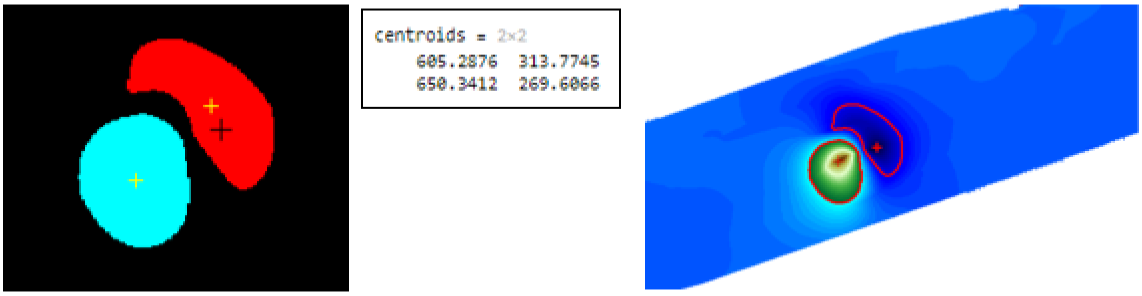

Fig. 4. Centroids determination and output image on an magnetic anomaly with outlines of detected anomaly (source: own study).

The spatial dimensions along with the determination of the positive and negative extremum of an anomaly at the first stage constitute the basis of the geoclassification method, described in the next chapter.

3. FERROUS OBJECTS CATALOG

The bottom objects with magnetic characteristics most often found in inland or marine waters include: ship wrecks, plane wrecks, car wrecks, gas and oil pipelines, power cables, containers, barrels, anchors, anchor chains, engines (airplanes, ships), -unexploded bombs (mines and bombs). Due to the fact that the method was developed in an inland water area - the basin of Odra river, where all the above-mentioned categories of objects are not present, there are too few of them to make a correct inference, or they appear in places additionally disturbed by the port infrastructure, the catalog was narrowed down to objects: shipwrecks, anchors, unexploded ordnance.

The first essential parameter that allows cataloging bottom objects due to their magnetic characteristics is the value of the magnetic anomaly that a given object induces. The theoretical value of the amplitude of the local magnetic field disturbance from a given object can be determined based on the Hall equation (Holt 2019). It is a value determined between the extremes of the anomaly – positive and negative value. In order to determine it, it is necessary to provide information on the size of the object: its length, width and weight, as well as information on the distance of the magnetometer above the object during the measurement.

$$\Delta M = 10 \cdot \frac{a}{b} \cdot \frac{w}{d^3} \tag{1}$$

where:

ΔM – magnetic anomaly amplitude (nT)
w – weight of the object (kg)
d – distance from device to potential object (m)
$\frac{a}{b}$ – length and width ratio.

Due to the fact that the value of an anomaly extremes is of major importance in determining which object a given disturbance may come from, it is the main parameter taken into account during object parameterization. It was observed that in case of shipwrecks, positive extreme is greater that negative; for the anchors both of them have similar value, and for the UXO is was observed that in many cases only positive extreme is induced, in some cases, the negative extreme is much lower (even 6-7 times) in relation to the positive extreme.

The next parameter is the value of the area occupied by individual anomalies on the map, separately for the area occupied by positive values and negative values. A certain tendency for these values to be consistent was observed, namely, in the case of wrecks, the area generated by negative values is larger than the area generated by positive values. In the case of unexploded explosives, the area it occupies on the map includes in some cases only positive values, or the area of negative values is extremely small. In the case of an anomaly due to anchors, was observed that both surfaces have similar area. For the purpose of statistical analyzes, the parameters of the length and width of the areas occupied by individual anomalies and their perimeters were also dimensioned, also divided into positive and negative areas of anomalies. No clear analogies were observed for individual classes of objects. As part of the parameterization, the centroids of individual anomalies were also determined, which were used at a further stage of the geoclassification method to indicate the geomagnetic location of objects on the map.

To sum up, the following parameters have been defined for the objects of individual categories:

- anomaly amplitude,
- minimum value of anomaly,
- maximum value of anomaly,
- area for positive values,
- area for negative values,
- length and width for positive values,
- length and width for negative values,
- positive centroids,
- negative centroids.

The final catalog consists of: 29 shipwerecks, 10 anchors and 79 UXO.

4. PARAMETRIC CLASSIFICATION

Based on the analyzes of theoretical materials, literature sources, and own observations and measurements, the geoclassification parameters were determined and the boundary conditions for the correct operation of the method were determined. During statistical analyzes while developing the catalog of objects, certain dependencies were observed between the values of the measured parameters of individual parts of the anomaly.

First of all, the amplitude value of the anomaly directly indicates the potential category of the object. Following the Hall equation, it is possible to determine the potential weight of ferromagnetic elements, and thus to fit it to a specific type of object. The second relationship that was observed is the ratio of positive to negative anomaly extreme. It has been observed that in the case of shipwrecks and large unexploded ordnance about the silhouette of the torpedoes, the value of the extreme positive is higher than the negative on average 3 times for shipwrecks and even 5 times or UXO. In case of underwater mines and small unexploded ammo, there is no negative extreme. Analyzing the cases of anchors, the similarity of the values of both extremes of the anomaly was observed.

The next parameter which was analyzed was areas for both parts of the anomaly separately. In case of shipwreck, both areas have irregular shape, and – what is a specific for that category of ferrous objects, the area for negative values was bigger than area for positive values. In case of small UXO and underwater mines, there was no negative area – due to the fact, there was no negative extreme at all. For large UXO, the area of positive value was even 5 times larger then for negative. In case of anchors both areas are in similar dimension. No other relationships were observed for the parameters of length, width or perimeter.

Due to the above, a classification method was developed based on the values of the ratio of the positive and negative extremes and on the basis of the area occupied by positive and negative values.

Analyzing the obtained images of the maps of the magnetic anomaly generated from the objects of the above-mentioned categories and taking into account the obtained spatial dimensions of individual objects from the catalog of objects, the following conclusions were drawn:

CATEGORY	CLAUSE
UXO	monopoly anomaly: - the most common case – i.e. most often there is no extreme of negative values and no area representing negative values dipole anomaly: - if there is a negative extreme, it is smaller than the positive extreme; - if there is a negative extreme, there is also a surface for negative values; - the area occupied by positive values is greater than the area occupied by negative values.
SHIPWRECK	dipole anomaly: - the value of the positive extreme is greater by the value of the negative extreme; - the area of the field occupied by positive values is smaller than the area occupied by negative values.
ANCHORS	dipole anomaly: - the value of the positive extreme is equal to or almost equal to the value of the negative extreme; - the area of the field occupied by positive values is equal to or almost equal to that occupied by negative values. the conditioning was determined on the basis of the relations: - the positive extreme to the negative extreme; - the area occupied by positive values to the area occupied by negative values; - the boundaries of the ratio condition were defined on the basis of the object catalog of minimum and maximum values.
OTHERS	objects that do not meet the above-mentioned conditions

5. VERIFICATION

The correctness of the parametric method was verified based on the real data obtained during the topic analysis. For this purpose, tests were carried out on the basis of 116 images of magnetic anomaly maps. Some of anomalies are induced by the objects buried in a certain layer of the bottom. For the category the following number of objects was tested: 26 shipwrecks, 7 anchors and 83 UXO.

The results are presented in matrix below (Fig. 3).

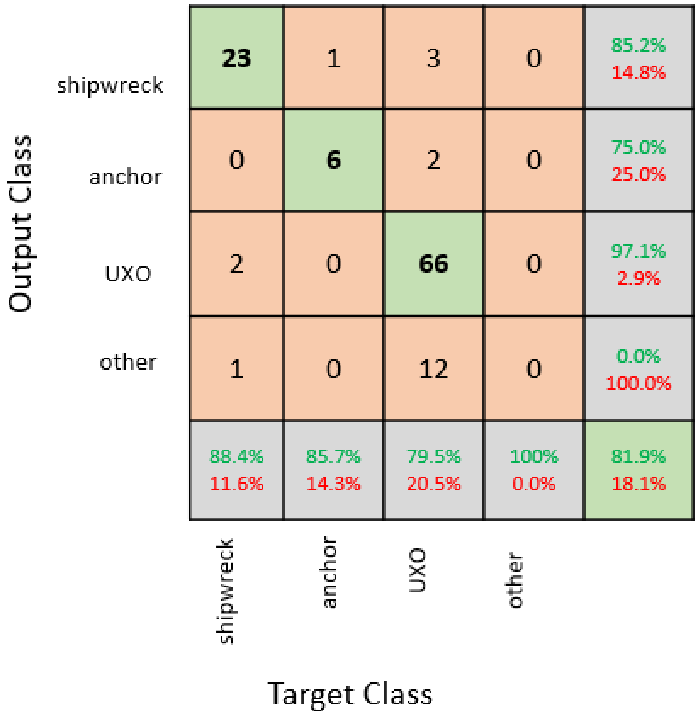

Figure 5. Confusion matrix (source: own study).

The above matrix presents the obtained results of the verification of the method. It is assumed to work correctly for 81.9%. In the case of the magnetic anomaly maps from the shipwrecks, the method worked in 88.4% correctly. For 2 cases, shipwreck magnetic anomaly was classified as UXO – due to the fact of the magnetic anomaly extreme`s values and for 1 as other due to the failure of the condition related to areas of positive and negative values. In the case of anchors, one anomaly has been classified as a wreck. This is due to the fact that the established limits of the value of both extremes and the condition related to the ratio of the positive to negative surface have been exceeded. As for UXO objects, 12 of them were recognized as the other category. This is due to the fact, that its negative extremes were greater than positive ones. Such situation takes place when objects are buried in a certain layer of the bottom, and method was developed for the objects lying on the seabed. Next misclassification: as an anchor in 2 cases and shipwreck in 3 cases, as in the case of the previous category, is associated with a slight exceeding of the limits and conditions of classification. To sum up, method is working correctly at the level of almost 82%.

6. CONCLUSION

The article presents a proposal for a method of classification of ferromagnetic bottom objects based on the analysis of the magnetic anomaly map imagery. The authors presented a hybrid method of image segmentation, consisting of, among others, thresholding, binarization, detection of anomaly edges, its numbering and dimensioning. The catalog of ferrous objects is presented. The clauses for parametric classification based on object`s catalog is proposed. Finally, the method's operation has been verified. The number of 116 objects participated in the verification, and the results of almost 82% of correctness is obtained. The method assumed operation on bottom objects so it can be concluded, referring to the verification results, that there should be specific limitation to use it.

For further works, authors assume an attempt to develop a geoclassification method based on fuzzy logic. For this purpose, it is necessary to obtain a much larger amount of data.

REFERENCES

1. Bodus-Olkowska, Izabela, i Janusz Uriasz. Segmentacja obrazu mapy anomalii magnetycznej akwenu dla celów detekcji i lokalizacji podwodnych obiektów ferromagnetycznych. Roczniki Geomatyki, t. 17, 1(84), Polskie Towarzystwo Informacji Przestrzennej, 2019.
2. Bodus-Olkowska, I., Uriasz, J., Ferromagnetic Underwater Target Detection Based on a Magnetic Anomaly Map. Geomatics and Environmental Engineering, 14(1), 2020. https://doi.org/10.7494/geom.2020.14.1.35.
3. Dimitriu, R.G., Barbu, M.B., Radu, O., Stanciu, I.M., Roșca, V., 2019, Marine geophysical investigations to assess the safety of the Romanian maritime space. Case study: Midia harbor offshore: 19th International Multidisciplinary Scientific GeoConference SGEM2019, Conference Proceedings, 19, 1.1, 873-881, 2019.
   ISSN 1314-2704, ISBN 978-619-7408-76-8, DOI: 10.5593/SGEM2019/1.1.
4. Dimitriu, R. G., Main results of marine gravity and magnetic researches carried out at GeoEcoMar. Geo-Eco-Marina, 25, 75–98, 2019. DOI:10.5281/zenodo.3607420.
5. Dharini S., Jain S., An efficient and hybrid pulse coupled neural network - based object detection framework based on machine learning, Computers & Electrical Engineering, Volume 96, Part B, 2021.
6. Dimitriu, R.G., Tchernychev, M., Lukic, Z., Barbu, B.M., A Magnetic Investigation of the Scuttled, German Danube Flotilla and of the Risks it Poses: 11th Congress of the Balkan Geophysical Society, Bucharest, Romania, October 10-14, 2021, Conference Proceeding Volume BGS2021, 2021.
   DOI: 10.3997/2214-4609.202149BGS83.
7. Holt P., Marine Magnetometer Processing, , 3H Consoulting Ltd., Plymouth, 2019.
8. Ibraheem, I.M.; Aladad, H.; Alnaser, M.F.; Stephenson, R., IAS: A New Novel Phase-Based Filter for Detection of Unexploded Ordnances. Remote Sens. 13, 2021. https://doi.org/10.3390/rs13214345
9. Kantsios V., Demonstration of Advanced Geophysics and Classification Technologies on Munitions Response Sites Fort Rucker, Alabama; Demonstration Report; ESTCP Project MR-201161, URS Group Inc., 2013.
10. Kantsios V., Helmilinger B., Hall D., King T., Demonstration of Advanced Geophysics and Classification Technologies on Munitions Response Sites Pole Mountain Target and Maneuver Area, Wyoming; Final Report; ESTCP Project MR-201161, URS Group Inc., 2012.
11. Kantsios V., Helmilinger B., Hall D., Demonstration of Advanced Geophysics and Classification Technologies on Munitions Response Sites Former Spencer Artillery Range Van Buren County, Tennessee; Demonstration Report; ESTCP Project MR-201161, URS Group Inc., 2013.
12. Khodayari-Rostamabad A., Reilly J. P., Nikolova N. K., Hare J. R., Pasha S., Machine Learning Techniques for the Analysis of Magnetic Flux Leakage Images in Pipeline Inspection, IEEE Transactions on Magnetics, vol. 45, no. 8, pp. 3073-3084, 2009.
    doi: 10.1109/TMAG.2009.2020160.

13. Kolster M. E., Døssing A., Scalar magnetic difference inversion applied to UAV-based UXO detection, Geophysical Journal International, Volume 224, Issue 1, , Pages 468–486, 2021. https://doi.org/10.1093/gji/ggaa483.
14. Mani V. R. S., Saravanaselvan A., Arumugam N., Performance comparison of CNN, QNN and BNN deep neural networks for real-time object detection using ZYNQ FPGA node, Microelectronics Journal, Volume 119, 2022.
15. Mattei, G., & Giordano, F., Integrated geophysical research of Bourbonic shipwrecks sunk in the Gulf of Naples in 1799. Journal of Archaeological Science: Reports, 1, 64–72, 2015. https://doi.org/10.1016/J.JASREP.2014.11.003.
16. Monteiro, A., & Costa, M., Underwater Archaeology with Light AUVs. Oceans, 2019. https://doi.org/10.1109/OCEANSE.2019.8867503.
17. Nazlibilek S., Kalender O., Ege Y., Mine Identification and Classification by Mobile Sensor Network Using Magnetic Anomaly, IEEE Transactions on Instrumentation and Measurement, 2011. DOI: 10.1109/TIM.2010.2060220.
18. Pearline A. S., Kumar S. V., Performance analysis of real-time plant species recognition using bilateral network combined with machine learning classifier, Ecological Informatics, Volume 67, 2022.
19. Pratt W. K., Introduction to Digital Image Processing, CRC Press, 2014. ISBN 978-1-4822-1669-1, 2014.
20. Pregesbauer M., Trinks I., Neubauer W., Automatic Classification of Near Surface Magnetic Anomalies – an Object Oriented Approach, 10th International Conference on Archaeological Prospection, 2013. DOI: 10.2307/j.ctvjsf630.131
21. Sadgrove E. J., Falzon G., Miron D., Lamb D. W., Real-time object detection in agricultural/remote environments using the multiple-expert colour feature extreme learning machine (MEC-ELM), Computers in Industry, Volume 98, 2018. ISSN 0166-3615, https://doi.org/10.1016/j.compind.2018.03.014.
22. Shivappriya S. N., Priyadarsini M. J. P., Stateczny, A., Puttamadappa, C., & Parameshachari, B. D. Cascade Object Detection and Remote Sensing Object Detection Method Based on Trainable Activation Function. Remote Sensing, 13, 2021, https://doi.org/10.3390/rs13020200
23. Tang Y., Ren F., Pedrycz W.,, Fuzzy C-Means clustering through SSIM and patch for image segmentation, Applied Soft Computing, Volume 87, 2020. ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2019.105928.
24. Underhay S. L., Vardy M. E., and Henstock T. J., Marine UXO detection: Critical analysis of the magnetic workflow, Symposium on the Application of Geophysics to Engineering and Environmental Problems, 2021, https://doi.org/10.4133/sageep.33-188
25. Xiang Z., Zhang R., Seeling P., Chapter 19 - Machine learning for object detection, Editor(s): Frank H.P. Fitzek, Fabrizio Granelli, Patrick Seeling, Computing in Communication Networks, Academic Press, 2020. ISBN 9780128204887, https://doi.org/10.1016/B978-0-12-820488-7.00034-7.
26. Zhao J., Xu Sh., Wang R., Zhang B., Guo G., Doermann D., Sun D., Data-adaptive binary neural networks for efficient object detection and recognition, Pattern Recognition Letters, Volume 153, 2022.