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ANALYSIS OF MODERN METHODS OF SEARCH AND CLASSIFICATION OF EXPLOSIVE OBJECTS

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Annotation. The article is devoted to the analysis of existing methods of searching for explosive objects on the surface of the earth and under it, and to the development of new effective approaches to solving the problem. We focus on developing solutions based on AI technologies and methods that use publicly available hardware, structural methods, and machine learning methods The problems and their solutions mentioned in the article are quite specific and, despite the relevance of the topic of searching for explosive objects, poorly developed. The main reason for this situation is either the lack of information in the public domain, when developments are carried out by military departments or private companies, or the relatively low development of countries that suffer from the problem of demining territories where military operations have been or are being conducted. From 2014 to 2022, on the territory of Ukraine, the area affected by explosive objects was approximately equal to the area of Croatia, which took 20 years to clear the territories after the war in the Balkans (1991–1995). After 2022, the territory affected by explosive objects increased several times. The intensity of shelling can currently be compared to the First and Second World Wars, so it is safe to say that the problem of finding explosive objects has reached a higher level. Therefore, considering the volume of data and the scale of the affected territories, we decided to study the main directions and modern methods of searching and classifying explosive objects in order to use them to create a system or a framework for solving the given task. The results of this article are planned to be used to create a single algorithmic environment for solving the problems of finding explosive objects, which, if necessary, will be able to process data from different sources of information, with different degrees of detail and depth.

Keywords: artificial intelligence, neural networks, machine learning, computer vision, recognition, explosive objects.

Introduction

The problem of recognizing explosive objects is of urgent importance for modern Ukraine and the future post–war period when thousands of unexploded ammunition and mines will remain. The area that is potentially dangerous can be incredibly large, and the number of dangerous munitions and other explosive objects is constantly increasing. The presence of plastic mines makes even tested areas dangerous in the future. Despite the work on demining and disposal of munitions, the dangerous area requiring analysis for explosive objects is 174 thousand square kilometers by the beginning of 2023, which is 30% of the total area of the state. The development of a mathematical model of the explosive object search system will allow for the creation of a remote search and monitoring system, as well as horizontal scaling of the search process.

State of the industry

Scientific findings from a broader topic – the identification of underground objects – is used in archeology, geology, construction, and other fields related to soil scanning. Private companies have their own developments that are not available to the public. Software and hardware are mostly focused on human interpretation, but with some data analysis and image enhancement, so it all depends on the quality of the images, the capabilities and settings of the software, and the experience of the person interpreting the data. The latest works in the field of determining the location of explosive objects focus not so much on inventing new methods, but on improving the results of existing ones, reducing energy costs, processing data from several types of sensors, using the cheapest possible equipment, etc. In Ukrainian science, this branch is poorly represented and is mainly focused on underwater demining and searching using the principle of a metal detector [5].

Analysis of existing approaches and methods

One of the most popular methods of detecting explosive objects are GPR (Ground Penetrating Radar) systems. They are popular all over the world and covered in many works. It is these methods that are mainly covered in this article. Attention is also paid to methods using infrared radiation and visual analysis.

In the article [1], the authors very widely and meaningfully analyze the existing approaches to the search for explosive objects, use different methods of identifying objects underground, apply different algorithms. The complexity of processing data from sensors is emphasized due to the variety of conditions when conducting experiments, the need to adjust the equipment to specific conditions, such as the type of soil, depth of mine laying, weather conditions, antenna frequency, etc.

Fig. 1. Appearance and principle of operation of GPR.

The large number of indicators that need to be considered when searching for mines leads to the need for a lot of computing power. Infrared (IR), electromagnetic induction (EMI), and ground penetrating radar (GPR) images are the most effective and simplest.

Among the disadvantages of the above IR methods, it can be noted that the accuracy of the search result is greatly affected by such factors as oncoming light, fog, rain, limited depth (the maximum depth is 20 centimeters), etc. EMI only detects metallic objects, while GPR requires a large amount of information to process and complex calculations. However, it is the GPR images that are worth paying attention to, given that deep learning technologies and the latest specialized computers reduce the computational complexity of this approach. In Fig. 2. the principle of GPR operation is given.

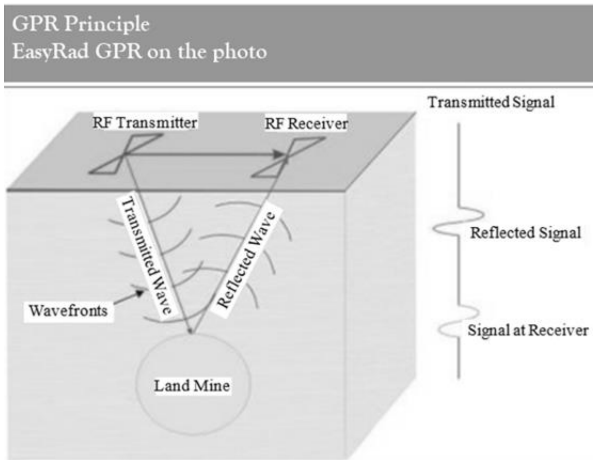

Fig. 2. Principle of GPR operation.

Among the common algorithms used in the search for explosive objects are the Method of Moments, the Fourier Method, the Long Line Method and other analytical methods. In the comparative table of the article [1] (table 1), it can be noted that the maximum depth for all methods is 20 centimeters, according to the ratio of the weight of the measuring complex, the type of objects (plastic and metal) to be determined, the height of the experiment (4 meters), GPR stands out, although it has the second most expensive cost according to the analysis from the article.

We believe that as one of several methods in further research, it is the analysis of GPR images that is worthy of attention for further research and analysis. For this, it is necessary to obtain or create datasets with so-called GPR B-scans, also called radagrams, in which objects underground are examined with the help of electromagnetic waves and visualized as hyperbolic patterns in two-dimensional space.

Radagrams are characterized by high complexity of interpretation, so their correct analysis requires the help of an industry expert. The use of the latest methods of deep learning (Deep learning), generation (a program for generating B-scans gprMax), augmentation, Generative Adversarial Networks will help properly train the model to identify the desired objects. At the same time, the experience of an industry expert is needed only during the training process. The GprMax synthesis program is often used to generate radagrams, but finding and creating real images for training will be considered a priority area for further research.

Table 1. Comparative characteristics of the methods

Method	Detected object	Application frequency	Maksimum detection height
Acoustic-sesimic	Plastic or mine cover	450 Hz sound wave	5 cm
GPR	Plastic or mine cover	1 - 5 GHz radio wave	20 cm
EMI	Metal mine cover	300 Hz - 2 GHz bandwidth secondary magnetic field	10 cm
IR	Plastic or metal mine cover	3 MHz - 140 GHz band range infrared wave	5 mm - 20 cm
NQR	Plastic or metal mine cover	0.5 MHz - 6 MHz band range radio wave	20 cm
TNA	Plastic or metal mine cover with its explosive	10 - 14 MeV energy electronsr	20 cm
Neutron backscattering	Plastic or metal mine cover with its explosive	10 - 14 MeV energy neutrons	20 cm
X-ray backscattering	Plastic or metal mine cover with its explosive	150 keV energy X-raysı	3 cm
MAD	Plastic or metal mine cover	1 - 25 kHz band AC source	20 cm

It should also be noted the complexity of building models for B-scans in the gprMax program [11]. Here, the emphasis is on creating artificial obstacles such as tree roots, rocks, and other objects when generating training images. Modern computers from NVidia, used in the field of autonomous driving and having extremely high computing power, can handle complex calculations when working with a large amount of data from GPR. The relatively small weight of the device for creating GPR images will allow using robots or drones.

In article [2], three neural networks are used for the analysis of radiograms (Fig. 3) to determine the shape of the object under the ground, material, and additional features, such as depth, size, etc. The authors note that currently many studies focus their attention on the recognition of cylindrical objects, while few have been engaged in the full classification of objects. The gprMax program [11] is used to generate the dataset, which is a de facto standard program for similar studies. According to the results of the work, the shape of objects is determined in an average of 90% of cases, the material in 99-100%, and the depth has a larger range of average error values - from 4 to 16 percent. The research has good results, but the approach using multiple neural networks is not flexible and requires constant addition or modification of existing networks.

The research also uses generated data. This approach is often used, but to get as close to reality as possible, real data is needed. The lack of a sufficient number of samples in datasets is a common problem in the subject area.

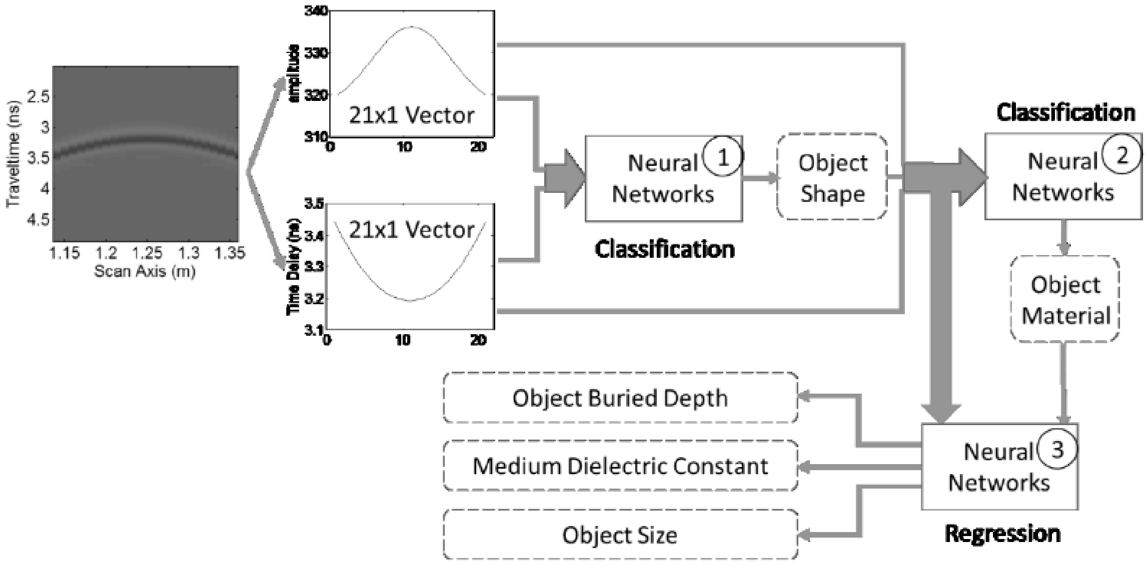

Fig. 3. General diagram of the system of 3 neural networks

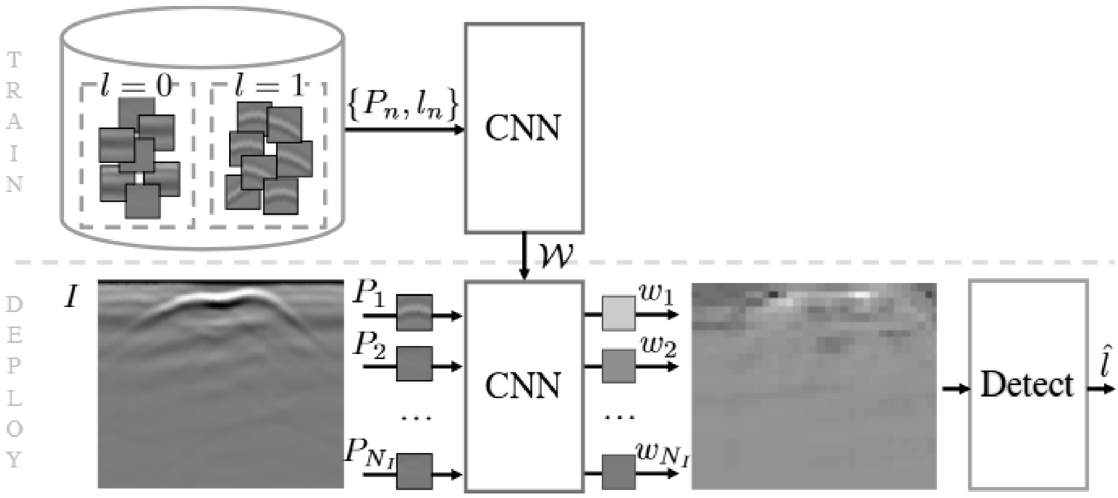

Fig. 4 Using convolutional networks (CNN)

The article [3] (Fig. 4) is devoted to the determination of mines underground, where it is proposed to classify the synthesized data (B-scans) according to the principle of presence/absence of mines. However, training is conducted at pre-prepared facilities. gprMax is used for testing. Moreover, as a result of testing, the accuracy is 95%. This method gives good results, but still, the analysis is performed only on synthesized images. However, as the authors themselves note, the 95% accuracy can be improved.

The use of deep learning methods is proposed in [4] (Fig. 5), where the authors study the problems of recognizing underground objects (on B-scans with GPR) on roads to detect gas accumulations, underground infrastructure, sewage, and water pipeline leaks, etc. Unlike many similar studies, the authors study not only the definition of hyperbolas on GPR B-images, but perform the classification of the entire range of images. Attention is also paid to obstacles such as hatches (these objects are removed from the analysis results). This study has excellent results, but is limited to use exclusively on roads. For classification, several sets (hatches, separating boundary of layers, hyperbola, soil) are selected, on which training takes place and additional processing is required when adding new classifiers.

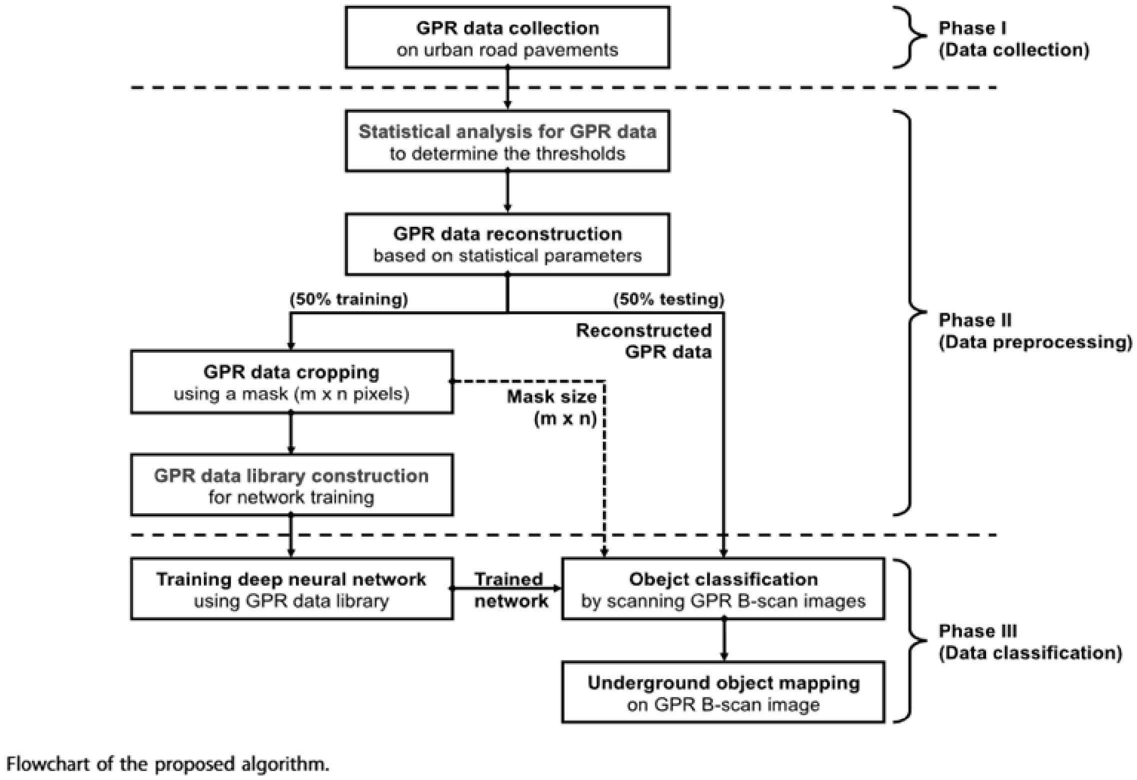

Fig. 5. Use of deep learning (Deep learning)

In study [6], the approach with 3-raw average subtraction is studied, and on the example of the application of two machine learning algorithms - KMeans and KNN - objects are detected with high accuracy. However, the working dataset is small and not aimed at creating problems in recognition, if images with a larger number of classes are added to the dataset, there is no certainty that the algorithms will produce the same high accuracy.

Groundwork was carried out by the authors in work [7], where they study the search for explosive objects from different angles (Fig. 6).

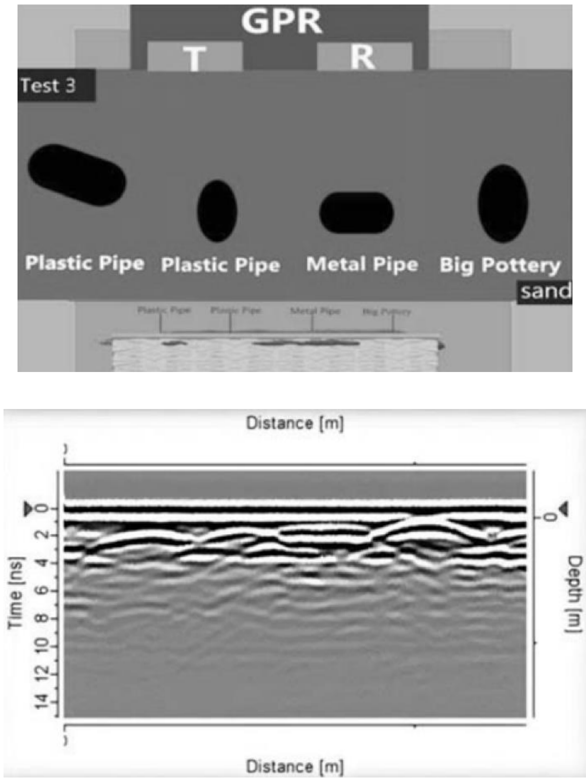

Fig. 6. Search for explosive objects from different angles

However, the analysis is performed by a person in the Rad Explorer software complex.

Summarizing the above-mentioned works using GPR, the following conclusions can be drawn:

- Datasets insufficient in size;
- The leading role of human in learning and identifying objects;
- The proof of the results is done experimentally, with limited and often artificial and adjusted datasets, and the obtained accuracy is questionable;
- A small number of classes take part in the classification of objects, that is, for new classes, algorithms will have to be redesigned, or layers of neural networks must be added, etc.;
- Deep learning approaches, for example, CNN, are trained on synthetic datasets, and those that are generally ideal and in real use may give larger errors.

Considering that GPR has a certain number of disadvantages, but is widely used in research [8], the authors of this paper plan to use GPR to search for explosive objects. However, before that, it is planned to investigate other two methods:

- search using a thermal camera;
- analysis of data from a regular video camera with high resolution.

Visual methods of detecting explosive objects using a camera are currently very relevant due to the large number of ground explosive devices in occupied and de-occupied territories of Ukraine, including in buildings, on the outside of structures, trees, etc. The article [12] gives an example of the construction of a cheap system used to search for explosive objects that are not visible on the surface. In the article [13], the authors create a system of visual recognition of explosive objects with the help of a robot, the accuracy of the determination is about 90%. The value of the results of this work also lies in a useful comparative analysis of some methods that we want to apply in further research - visual search and ground scanning. Moreover, the infrared cameras presented in Table 2 differ from the thermal cameras mentioned above. Unlike active infrared radiation, a thermal camera is passive, and its accuracy does not depend on weather conditions.

Table 2. Comparative characteristics of the methods

Sensing Technique	Cost	Energy Consumption	Quality of Images	Usability under Various Weather Conditions	Ground Penetration	Object Material Independency
Camera	✓	✓	✓	✓	x	✓
Infra Red	✓	✓	x	x	✓	x
Ultrasound	✓	✓	x	✓	✓	✓
Ground Penetrating Radar	x	x	x	x	✓	✓

A camera using thermal sensors has been little researched. It is often confused with an infrared camera. Recently, this direction is considered one of the most promising methods [9], the work [10] considers the use of drones equipped with thermal cameras (Thermal imaging systems). CNN is used for data analysis. The article does not reveal the details of the study, there are no results.

Unlike active infrared cameras, which use the properties of short-wave infrared radiation, thermal cameras are passive and recognize medium and long-wave infrared light.

We consider this technology worthy of attention in further work.

Conclusions and direction of further work

The information analyzed during the preparation of this article allows us to conclude that no single method is sufficient for the maximum disposal of all explosive objects on the territory of Ukraine. We consider the most promising methods to be methods that use images from video-thermal cameras and GPR. The availability of industrial unmanned aerial vehicles (UAVs) allows the combination of equipment and the use of various information to search for explosive objects, the research aims to remove the human from decision-making, as well as to minimize participation in the learning process. The possibility of covering large areas with a diverse landscape gives hope for the maximum cleaning of our country from explosive objects.

The results of this article are planned to be applied to create a common algorithmic environment, a framework that allows the use of several algorithms to solve the problems of finding explosive objects. For each approach, have a solution that will have one or another application. Depending on the set accuracy, it is possible to obtain the desired accuracy or depth of detection by increasing the number of methods. For example, to search for PMF1, the so-called "petals" [14], visual information is sufficient,

Fig. 7. PMF 1 and visual scanning

However, if there is snow on the ground, you need to add a thermal camera for the same task, if you want to scan more than, say, 10 cm, you need to add a ground scanning radar (GPR).

For the maximum effect for the search for explosive objects, it is suggested to present the result in the form of the following sets or classes:

- missing objects at all;
- objects are present, but they are not explosive;
- it is uncertain whether explosive objects are present or not;
- explosive objects are present.

Such separation will allow building application systems of various nature. For example, the first and second classes will make it possible to lay routes through minefields, while the third and fourth classes will allow to build accounting systems of dangerous objects for further demining.

Or you can apply a similar division into classes, but slightly differently, as in Table 3:

Table 3. Breakdown of results into classes

Non-explosive objects are present	Explosive objects are present
There are no explosive objects	There are no explosive objects

To improve training, it is planned to apply Generative Adversarial Networks (GANs) and data augmentation, gprMax will help to enrich the datasets (in the case of using GPR).

Possible obstacles during the study:

- If the enemy aims to create an obstacle to detect an explosive object, it will be difficult to bypass, so you will have to add processing of other sensors, such as electromagnetic field measurement, infrared sensors, etc. Such objects should be assigned to the third class (it is uncertain whether explosive objects are present or not);
- Homemade explosive devices must also be taken into account, so objects such as pieces of pipes, cans will fall into false-positive and vice versa, homemade mines will be classified as pieces of pipes, etc., i.e. false-negative classes (see the confusion matrix in the table 4);

Table 4. Prediction results (confusion matrix)

Predicted Value (predicted by the test)		Actual Value (as confirmed by experiment): positives	Actual Value (as confirmed by experiment): negatives
	positives	**TP** True Positive	**FP** False Positive
	negatives	**FN** False Negative	**TN** True Negative

- Searching a large dataset is a very important issue, training on synthetic data can lead to a noticeable error;

Possible developments and enhancements:

- creating a system that, in case of difficulties in identifying the object, can adjust the equipment, for example, for deeper scanning, or scanning under all courses;
- analysis of 3D structures;
- involvement of volunteers with their equipment, on which the software will be installed;
- Building a framework capable of using several sources of information to increase the accuracy of the determination.

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