Conceptual design of an autonomous rover with ground penetrating radar: application in characterizing soils using deep learning

P. Linna[a], N. Narra, J. Grönman[a], A. Halla[a], T. Aaltonen[b]
[a]Computing Sciences Unit, ITC Faculty, Tampere University, Pori, Finland
[b]Satakunta University of Applied Sciences, Pori, Finland
petri.linna@tuni.fi

***Abstract* - In the pursuit to make agricultural production efficient, the earliest farmers used data in the form of notes of observations. In the current age of data, it has become easier to collect data over a wide spectrum of parameters. There are numerous sensing technologies for measuring processes and parameters over the field surface, typically mounted on satellites, aerial (drone), ground vehicle and static platforms. In the latest understanding, soil is gaining increasing attention and recognition for its significance in not only increasing productivity but also stabilizing the environment. However, characterizing soil in a field is not trivial, especially when required to access the deeper layers and quantifying the essential contents – water, nutrients and organic matter.**

This paper presents a short review of applications of ground penetrating radars (GPR) in measuring soil content and structure. The focus is on deep learning constructs that have been used for interpreting and establishing correlations. The review serves to inform design considerations for a planned autonomous rover that will be used for surveying field soils in the Satakunta region of Finland.

Keywords - autonomous rover, ground penetrating radar, soil, deep learning

I. Introduction

The data is increasing continuously in the agriculture and big data will have big role in near future [1]. For example the satellites collect huge amounts of data with numerous special cameras and the farmers' own work machines also produce many kinds of data. Some of these data are openly available, the part are commercials and part are the farmers' own private data of the farm. The challenge is that how the farmers can to utilise these different sources as effectively as possible and can to move them in practice in the farm.

A. MIKÄ DATA project

In the MIKÄ DATA project, which belongs to the EIP-AGRI group and funded by the European Agricultural Fund for Rural Development, started to build intelligent data service for the farmers [2]. The Data oriented field managements will help farmers to do more accurate growing planning. The project focused on the variations of soil and nutrients for visualising and developing of the algorithms of yield forecast based on convolutional neural networks (CNN) technique [3]. Large numbers of data were collected from 100 hectares for example a special soil scanning equipment (Veristech), drone with multispectral camera and soil samplings. In the project were made significant and promising results to utilise new technologies like artificial techniques (AI). The large data amounts of fields mean that they must be more effectively analysed with the help of the AI. It is not possible for the farmers to analyse all that data.

B. Data steps of field health

In the dialogues with farmers, the most essential starting point to evaluate the field health is altitude structure. Water should not remain to stand to the field, but neither flow too fast away along the surface. The drainage can be used to solve main moisture problems, but it doesn't fix all of them. So essential is to get exact information of field altitude structure, so farmers can make the necessary corrections. Second essential thing is to know the location of the existing subsurface drainage (if there are no exact maps available or they are not even found anywhere) and its functionality. From Sentinel-2 satellite can get moisture maps which can help to evaluate the moisture variation inside the field and find the moisture problems. The drone with the hyperspectral camera can collect accurate moisture information, but it requires expensive special equipment. In both cases are measured only surface moisture, not inside of soil.

C. PeltoAI and BioEväät projects

So, the determination of the condition of the field should be begun with the checking of altitude structure, subsurface drainage and moisture structure. These and many other following stages are studied in the PeltoAI project. In the parallel BioEväät project will be made corrective actions to problems that have been found. The goal is to understand the functionality of the soil with more exactly via data. In the near future, it is also more important to get more exact data to follow the amount of carbon in the field. Because of climate change and to confirm field health based also on carbon amount.

D. *Paper objectives*

At the very general level, the vegetation of the field needs water, heat and nutrients. At the next much more exact level, the need to know soil types, the condition of drainages, the condition of the granular structure, pH-values and humus content. From the point of view of above mentioned projects it is still unclear what is an order of importance. It is still impossible to measure all these values cost-effectively with the particularly very good precision at a practical level. The motivation of this paper was that with GPR can locate drainages and their condition and the soil tightness values, and data analyses can do more automatically with AI.

One of the objectives of this paper is to find new kind of potentiality of GPR-technique to measure and understand soil functionality and structure. So, we assume that data can be collected using old technique but use new AI techniques to analyse that data. The starting point is that the evaluation of the condition of the field would be as advantageous as possible but still of high quality and diversify. The precision farming has long been talked about but accurate information about soil features and its condition would still be needed more and more.

II. GPR

The GPR technique is an old invention and it has been utilized in the analysis of the condition of fields. GPR uses electromagnetic radiation and microwave band, which range are 10 MHZ to 2.6 GHz. GPR data is very open to various interpretations because of its analysis have been made by hand, which is laborious, particularly in the big data amounts.

A. *GPR in agriculture*

The GPR technique has been in many ways researched and utilised in the fields. Illawathura et al. has been studied soil moisture with GPR data [4]. The drainage pipes have been examined for example by Allred et al. [5], but drainages pipes can also find with unmanned aircraft [6] and with thermal infrared imagery [7]. De-Ville et al has studied soil compaction [8]. Akinsunmade et al. [9] has studied the correlations of agrotechnical properties of the different soil more widely. New interesting research openings are the measurement of the fine roots of agricultural crops [10]. With the measurement of the roots, the evaluation of the amount of the carbon would be achieved. Shen et al. [11], did quantification for soil organic carbon with GPR. The roots change to carbon during time and improve soil that way, depending on soil type and depending on the cultivation methods. The carbon will rise the growth and condition of the field.

Thus, it appears that GPR has been widely used in agriculture on this basis, such as moisture measuring, soil stratigraphy, layers thicknesses and calculate root biomass [12].

Nowadays, GPR measuring can do also with drones. Koganti has measured the drainage of the field with drone [13]. Rodriguez et al. [14] used drones to measure moisture.

Surprisingly, so far, our study did not find any research paper which uses the AI analysis of GPR data in the agriculture sector.

III. GPR AND AI REVIEW

The table below lists the papers containing the GPR and AI terminology. The findings of papers are briefly discussed below.

TABLE I

Paper	Target	Data	AI-tech	Year
[15]	Layer properties: thickness, permittivity	gprMax	ML, NN	2009
[16]	simulate GPR data	A-scan, gprMax	NN	2018
[17]	cover depth and diameter of rebar, moisture content	simulated	ML, forward solver, 120 layers	2019
[18]	corrosion, infrastructure monitoring	B-scan, gprMax	DL, u-net, cgan, encoder-decoder	2018
[19]	Bridge deck evaluation (thickness, moisture, rebar locations, corrosion)	many GPR equipments	HOG features	2016
[20]	detection of hidden surface crevasses on glaciers	GPR images from Antarctica	Support vector machine	2012
[21]	objects	B-scan, gprMaxToolBox, Citar-10database	Faster-RCNN	2018
[22]	objects	GPR	support vector ML and H-alpha decomposition	2018
[23]	landmines	B-scan	CNN	2018
[24]	Water content and its prediction	A-scan	CNN	2019
[25]	Small targets, Holographic subsurface penetration	?	DL, SR-CNN, bicubic, PDM, WIM, NSRCNN	2017
[26]	mines	UWB-SAR, simulated SAR images	CNN (two subnetwork decomposition, classification)	2018
[27]	debonding, pavement monitoring	A-scan	Support vector ML	2017
[28]	landmines	L-band	DL, CNN	2019
[29]	objects, tightness	rail	Wavelet NN, De-noising, 3 layers feedforward NN	2015
[30]	underground utilities	B-scan/A-scan	not AI yet	2018
[31]	pipes, cables and those track course	B-scan? Data generator, Ultra wideband GPR	ML	2018
[32]	landmines	B-scan, real-data	CNN	2017
[33]	deep and shallow crevasses	GPR dataset	ML, HOG	2019
[34]	objects	FDTD-simulated	DL, 9 layers CNN	2018
[35]	Explosive objects	A- and B-scan, test data: Grayscale images	CNN	2017
[36]	objects	Ultrawideband	CNN, 3 layers	2019
[37]	objects	3D, including B,C and D-scan	DL underground object detection, triplanar DCNN	2019

A. *Targets*

On the above table I, in the target-section, is estimated of the current research paper targets areas. It was not able to estimate exact targets from some papers. Those cases the column is labelled generally just “objects”. Many different targets were found. The most essential findings, from the point of view of the developing of the robot, were the moisture and the tightness. The measurement of the moisture with the help of GPR is an interesting application which has surely an advantage in the agriculture. With the help of this technique a more exact understanding of the moisture structure of the whole field would be obtained. The measurement of the tightness is an important finding because it can be used to estimate the excessive tightening of the field which affects the absorption of the moisture and to the possibilities of the growth of roots. Furthermore, there were the papers which focused on find drainage and their condition, but an AI had not been utilised.

B. Data

In the many researched papers had been utilised simulated data. The gprMax tool, which is open source software, was the most superior of these. It can be used to produce the GPR pictures without real equipment. This makes the data production very quick.

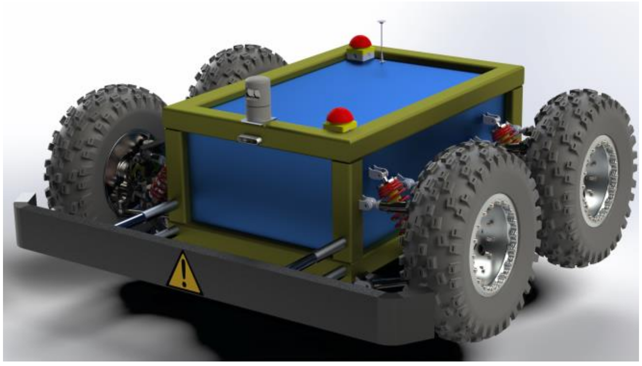
With GprMax tool produced data has been obviously already ready classified. It is essential that the data is of classified and high quality correct so it can then utilise for learning material of AI.

C. AI

A large amount of work of deep learning applications on GPR data has been in the detection of buried objects – ranging from utility pipes to mines (munitions). The primary task in such applications is classification and not a recreation of images from the radargram. Image synthesis networks have been used in other fields and Alvarez & Kodagoda [18] have explored its application to recreating sub-surface permittivity maps from b-scans. They have also hypothesised on the usage of LSTMs in combination with their generative network to leverage the sequential nature of the scans. Detecting objects is not the primary concern in soil characterization apart from the detection and tracing of sub surface drains in the fields. Of greater interest are – water and roots.

IV. AUTONOMOUS GPR ROVER: CONCEPTUAL DESIGN

Different kinds of mobile robots/rovers are more generally used for data collection in a variety of environmental applications, as the robot is seen as a promising tool for enhancing environmental data collection. Our goal was to design all-terrain rover, which is based on custom-made chassis, various sensors (GPS, GPR, LiDAR and RGB-D cameras) and ROS (Robot Operating System) as software which connects all hardware/software-connections. Prototype rover model was created in Solid Works modelling software, which can be seen picture 1.



Picture 1, prototype rover model.

A. Hardware

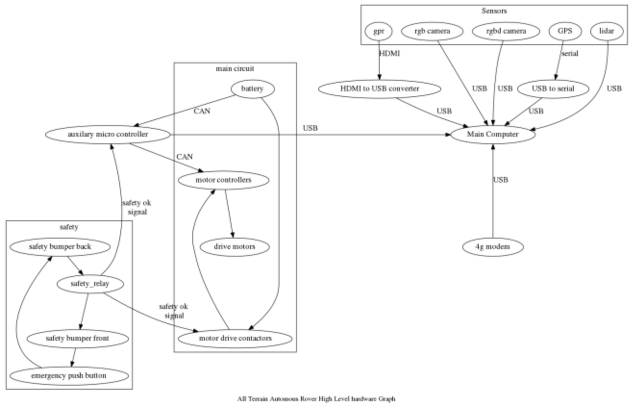
The body of the rover is made and welded of structural steel. The model has a diameter of 1200 mm x 800 mm x 500 mm. The tires are designed for off-road vehicles. Like all-terrain vehicles, the rover also uses steering and suspension.

For drive motors, the vehicle uses 48V 1kW servomotors in the gearbox for every 4 tires. A smaller 300W servo motor is used to control the vehicle. The voltage system was chosen to be 48V to keep the current proportional efficiency low, but in the area where ready battery systems are available, the voltage is within the safe voltage range. The battery was selected for reliability and voltage near the motors rated voltage. The LG Chem RESU Lithium-ion battery system has IP55 protection and is intended for outdoor use. It has a capacity of 13 kWh to operate the vehicle for approximately 2.5 hours with all engines running at full speed.

The security system consists of an industrial class safety relay and an overlapping safety circuit. The circuit consists of an emergency stop button and a safety buffer at the front and rear. The rover can also be stopped by remote control, but it is not permanently connected. The safety relay switches off the main power of all motors and actuators and sends a remote alarm. The operation can only be resumed when the safety relay is reset by pressing a button physically located in the rover.

There were a couple of options for computer hardware, either switching to ARM-based single-board computers (SBC), such as Raspberry Pi or Jetson Nano, or alternatively using x86-based computers. For each of these options, there are examples of robots and easy-to-assemble ROS packages. In our experience, single-board computing power is still limited when running a full on-board navigation and observation stack, and cloud-based systems still have the same problems as latency.

The main reason to go for single-board computers is power consumption, which is notably smaller than x86-based computers. If single-board computers use 20-40W power, a full-size x86 computer with medium-sized GPU consumes 300-500W. Other reason is the cost. Where Raspberry Pi can be bought for 40 euros and Jetson Nano for 100 euros, the full x86 computer setup with battery powered power supply and the average consumer grade GPUs are about 500 - 1000 euros. In this case, with a planned platform cost is 20,000 euros, so the price difference is not the main consideration. The drive motors are 1 kW and at peak power, with all engines running at full power, the power consumption is 4 kW while running, so the power consumption of the x86 computer is not a major limitation of the application. The connections between sensors, computer, main and safety circuits can be seen in picture 2.



Picture 2, connections.

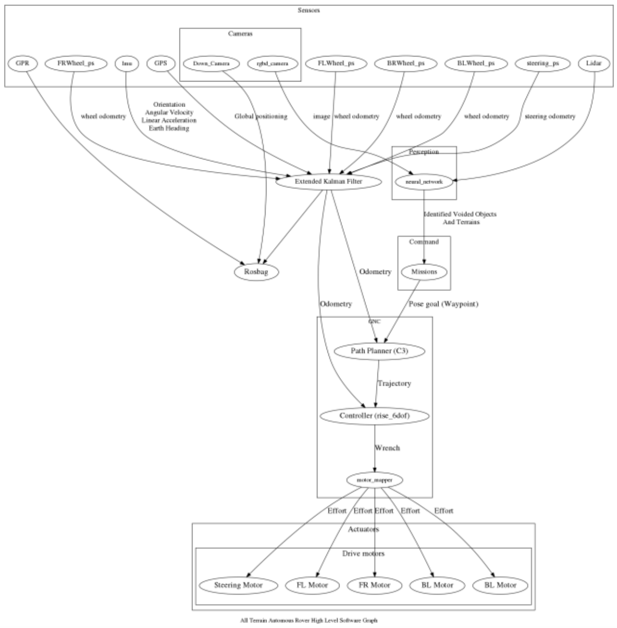
B. *Software*

ROS was chosen as the software platform, as there are already several implementations of ROS-based mobile robots in both research and production. Many open source software components and drivers have already been implemented in ROS. Another reason was authors previous experience about the ROS system. The ROS system is modular in nature and consists of different nodes, and communication between nodes takes place through topics, services and actions.

Localization is divided into two scales, global and local. Globalization is done by GPS, and this is used more for mission-level navigation. Localization is used to detect unknown terrain and obstacles. This is done with Depth Cameras (RGBD), LiDAR and the Inertia Measurement Unit (IMU). The rover monitors the tilt of the IMU to handle the tilt on inclines. The biggest challenge here is isolating the driven vegetation, but the LiDAR may seem like a solid barrier, as the vehicle in question probably needs a camera and a neural network based object detection. For new environments, data must be collected and the identification network trained several times before a proper generalization can be achieved. Global location senses are fused with the robot_localization package, which is a universal sensory fusion package that includes an extended Kalman filter and non-scented Kalman filter nodes.

The controller is using an open source implementation of a single robust integral of sign the error (RISE) algorithm developed at the University of Florida [38]. The path designer calculates the desired direction and velocity from the material position and the desired position. The engine mapping calculates the required forces for different engines and can tolerate engine failures of 1-2 depending on faulty engines. Missions are performed asynchronously and multiple tasks can be executed simultaneously. One task always detects and avoids dangerous objects. One checks the vehicle's stability and slows down the vehicle if the posture is unstable.

GPR data is captured from HDMI image using HDMI to USB capture card. The capture card appears on the Linux system as a webcam and is connected to the ROS via the usb_cam package. Analysis of GPR data can be done in almost real-time in rover or logged for offline use. Data is logged in rosbag, which is a handy ROS tool that can store messages on the screen so all sensory data and locations can be played back in order or used for analysis. The Rosbag video stream can also be easily cut into image sequences, and time stamps and image numbers can be converted to a csv file. The vehicle can also store GPR and RGB images from the same location for analysis. Connections can be seen in picture 3.



Picture 3, Software graph.

V. CONLUSION

In this paper, first described many GPR using targets in agriculture, the most important them were moisture and tightness measurements. This research finds out that data can be collected also by visualising like with gprMax tool. Classified and large amount of data is very important for CNN development and simulated data will have remarkable help for that work. In this paper was made short review of over twenty papers included GPR and AI keywords. So far, there didn't any papers of agriculture sector including CNN technique, so this sector will need deeper paper search and research. According of this review, we noticed that CNN technique is not very largely used in GPR data.

In this paper was described ROS robot architecture. The goal is developed functional robot and use it in the fields next year. Before that robot, CNN can be tested with simulated data.

These all findings will help our projects (PeltoAI and BioEväät) to understand more deeply field health and recommend the fields of farms repairing actions if needed.

Very interesting findings were drones, which are a potential vehicle to carry GPR equipment and enable make fields measurements very rapid. Second findings, root scanning with GPR technology will help understand the field more deeply and somehow to assists of the climate change control, because there is also a need to valuate biomass in the ground, not just over the field surface.

REFERENCES

[1] S. Ge. L. Wolfert, C. Verdouw and M.-J. Bogaardt, "Big Data in Smart Farming – A review" 2017, Agricultural Systems, 153, 69–80.

[2] P. Linna, N. Narra and J. Grönman, "Intelligent data service for farmers," 2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 2019, pp. 1072-1075.

[3] N. Narra, P. Nevavuori, P Linna and T Lipping, "A Data Driven Approach to Decision Support in Farming", EJC 2019, pp. 175-185

[4] Illawathura, Chameera, Parkin, Gary, Lambot, Sébastien, Galagedara, Lakshman, "Soil Moisture Estimation from GPR Hyperbola Fitting in the Agricultural Root Zone". CSBE/SCGAB AGM and Technical Conference 2019 (Vancouver, British Columbia, Canada, du 14/07/2019 au 17/07/2019). In: Book of Abstracts, 2019

[5] Allred, B., Wishart, D., Martinez, L., Schomberg, H., Mirsky, S., Meyers, G., Elliott, J., Charyton, C., "Delineation of Agricultural Drainage Pipe Patterns Using Ground Penetrating Radar Integrated with a Real-Time Kinematic Global Navigation Satellite System". Agriculture 2018, 8, 167.

[6] Robert Freeland, Barry Allred, Neal Eash, Luis Martinez, DeBonne Wishart, "Agricultural drainage tile surveying using an unmanned aircraft vehicle paired with Real-Time Kinematic positioning—A case study", Computers and Electronics in Agriculture, Volume 165, 2019, 104946, ISSN 0168-1699

[7] https://www.ocj.com/2018/07/using-drones-to-find-drainage-pipes/, refered 21. february 2020.

[8] De-Ville S. Pattison I. and Frost M., "COMPACT: A frequency analysis of Ground Penetrating Radar to identify agricultural soil compaction.", AGU Fall Meeting Abstracts, 2018, eid NS13B-0596

[9] Akinsunmade, A., Tomecka-Suchoń, S. & Pysz, P. Correlation between agrotechnical properties of selected soil types and corresponding GPR response. Acta Geophys. 67, 1913–1919 (2019).

[10] Liu, X., Dong, X., Xue, Q. et al. "Ground penetrating radar (GPR) detects fine roots of agricultural crops in the field". Plant Soil 423, 517–531 (2018).

[11] Shen, X., Foster, T., Baldi, H., Dobreva, I., Burson, B., Hays, D., Tabien, R., Jessup, R., "Quantification of Soil Organic Carbon in Biochar-Amended Soil Using Ground Penetrating Radar (GPR)". Remote Sens. 2019, 11, 2874.

[12] Katerina Zajícová, Tomas Chuman, "Application of ground penetrating radar methods in soil studies: A review", Geoderma, Volume 343, 2019, Pages 116-129, ISSN 0016-7061

[13] Triven Koganti, Ehsan Ghane, Luis Rene Martinez, Bo V. Iversen and Barry J. Allred, "Mapping Subsurface Drainage in Agricultural Areas Using Unmanned Aerial Vehicle Imagery and Ground Penetrating Radar ", 2019, Indian Near Surface Geophysics Conference"

[14] Wu, K., Rodriguez, G. A., Zajc, M., Jacquemin, E., Clément, M., De Coster, A., & Lambot, S., "A new drone-borne GPR for soil moisture mapping", 2019, Remote Sensing of Environment, 235, 111456.

[15] S. Caorsi and M. Stasolla, "A machine learning algorithm for GPR sub-surface prospection," 2009 Mediterrannean Microwave Symposium (MMS), Tangiers, 2009, pp. 1-5.

[16] I. Giannakis, A. Giannopoulos and C. Warren, "A Machine Learning Approach For Simulating Ground Penetrating Radar," 2018 17th International Conference on Ground Penetrating Radar (GPR), Rapperswil, 2018, pp. 1-4.

[17] I. Giannakis, A. Giannopoulos and C. Warren, "A Machine Learning-Based Fast-Forward Solver for Ground Penetrating Radar With Application to Full-Waveform Inversion," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 7, pp. 4417-4426, July 2019.

[18] J. K. Alvarez and S. Kodagoda, "Application of deep learning image-to-image transformation networks to GPR radargrams for sub-surface imaging in infrastructure monitoring," 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), Wuhan, 2018, pp. 611-616.

[19] P. Kaur, K. J. Dana, F. A. Romero and N. Gucunski, "Automated GPR Rebar Analysis for Robotic Bridge Deck Evaluation," in IEEE Transactions on Cybernetics, vol. 46, no. 10, pp. 2265-2276, Oct. 2016.

[20] R. M. Williams, L. E. Ray and J. H. Lever, "Autonomous robotic ground penetrating radar surveys of ice sheets; Using machine learning to identify hidden crevasses," 2012 IEEE International Conference on Imaging Systems and Techniques Proceedings, Manchester, 2012, pp. 7-12.

[21] M. Pham and S. Lefèvre, "Buried Object Detection from B-Scan Ground Penetrating Radar Data Using Faster-RCNN," IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, 2018, pp. 6804-6807.

[22] H. Zhou et al., "Combination of Support Vector Machine and H-Alpha Decomposition for Subsurface Target Classification of GPR," 2018 17th International Conference on Ground Penetrating Radar (GPR), Rapperswil, 2018, pp. 1-4.

[23] F. Picetti, G. Testa, F. Lombardi, P. Bestagini, M. Lualdi and S. Tubaro, "Convolutional Autoencoder for Landmine Detection on GPR Scans," 2018 41st International Conference on Telecommunications and Signal Processing (TSP), Athens, 2018, pp. 1-4.

[24] J. Zheng, X. Teng, J. Liu and X. Qiao, "Convolutional Neural Networks for Water Content Classification and Prediction With Ground Penetrating Radar," in IEEE Access, vol. 7, pp. 185385-185392, 2019.

[25] Y. Zhang, Z. Xiao, L. Wu, X. Lu and Y. Wang, "Deep learning for subsurface penetrating super-resolution imaging," 2017 10th UK-Europe-China Workshop on Millimetre Waves and Terahertz Technologies (UCMMT), Liverpool, 2017, pp. 1-4.

[26] T. H. Vu, L. Nguyen, T. Guo and V. Monga, "Deep network for simultaneous decomposition and classification in UWB-SAR imagery," 2018 IEEE Radar Conference (RadarConf18), Oklahoma City, OK, 2018, pp. 0553-0558.

[27] S. S. Todkar et al., "Detection of debondings with Ground Penetrating Radar using a machine learning method," 2017 9th International Workshop on Advanced Ground Penetrating Radar (IWAGPR), Edinburgh, 2017, pp. 1-6.

[28] F. Giovanneschi, K. V. Mishra, M. A. Gonzalez-Huici, Y. C. Eldar and J. H. G. Ender, "Dictionary Learning for Adaptive GPR Landmine Classification," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 12, pp. 10036-10055, Dec. 2019.

[29] Xiao-Li Chen, Mao Tian and Wen-Bing Yao, "GPR signals de-noising by using wavelet networks," 2005 International Conference on Machine Learning and Cybernetics, Guangzhou, China, 2005, pp. 4690-4693 Vol. 8.

[30] E. Skartados et al., "Ground Penetrating Radar Image Processing Towards Underground Utilities Detection for Robotic Applications," 2018 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO), Prague, Czech Republic, 2018, pp. 27-31.

[31] D. Seyfried, A. Busche, R. Janning, L. Schmidt-Thieme and J. Schoebel, "Information extraction from ultrawideband ground penetrating radar data: A machine learning approach," 2012 The 7th German Microwave Conference, Ilmenau, 2012, pp. 1-4.

[32] S. Lameri, F. Lombardi, P. Bestagini, M. Lualdi and S. Tubaro, "Landmine detection from GPR data using convolutional neural networks," 2017 25th European Signal Processing Conference (EUSIPCO), Kos, 2017, pp. 508-512.

[33] B. Walker and L. Ray, "Multi-Class Crevasse Detection Using Ground Penetrating Radar and Feature-Based Machine Learning," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 3578-3581.

[34] J. Sonoda and T. Kimoto, "Object Identification form GPR Images by Deep Learning," 2018 Asia-Pacific Microwave Conference (APMC), Kyoto, 2018, pp. 1298-1300.

[35] D. Reichman, L. M. Collins and J. M. Malof, "Some good practices for applying convolutional neural networks to buried threat detection in Ground Penetrating Radar," 2017 9th International Workshop on Advanced Ground Penetrating Radar (IWAGPR), Edinburgh, 2017, pp. 1-5.

[36] M. Elsaadouny, J. Barowski and I. Rolfes, "The Subsurface Objects Classification using a Convolutional Neural Network," 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 2019, pp. 0874-0877.

[37] N. Kim, S. Kim, Y. An and J. Lee, "Triplanar Imaging of 3-D GPR Data for Deep-Learning-Based Underground Object Detection," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 12, no. 11, pp. 4446-4456, Nov. 2019.

[38] N. Fischer, D. Hughes, P. Walters, E. M. Schwartz and W. E. Dixon, "Nonlinear RISE-Based Control of an Autonomous Underwater Vehicle," in IEEE Transactions on Robotics, vol. 30, no. 4, pp. 845-852, Aug. 2014. doi: 10.1109/TRO.2014.2305791