Localisation and Detection of Buried Objects like Mines in Diverse Soils with Softcomputing Methods

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Abstract. Originally, mines were detectable because of their more or less high metal content. Unfortunately, in the fast developing mine technologies, new materials that may last for many years, have made it possible to produce varieties of mines that are practically undetectable with the existing methods because of very low metal contents. As we showed, this fact can be caught with special pre-processing and classification structures like hybrid neural nets also if non destructive systems as common metal detectors are used. Also the existence of large numbers of landmines poses a several problems. Here also adaptive learning techniques, including neural nets can be considered as a possible solution, as they extract features from the ground bounce-removed responses and input this feature set automatically and can be empowered in field for new classification concepts.

The hybrid classification structure we developed and tested consists of self organizing memories (SOMs) and Backpropagation nets combined with the inter-neural WHU-Structures, whereby special pre-processing methods like DLS and fitting-methods are used to extract the feature specific items.

Introduction

Research has shown that soil physical properties can have important effects on various sensors used in landmine detection systems. These properties in turn control properties such as electrical conductivity, dielectric constant, thermal conductivity, and heat capacity, which directly effect sensor performance and which can be highly variable in space and time. The development of a mine detection system capable of detecting and classifying various types of mines under different environmental conditions presents many technical problems [1].

However, in practice, they have been only partially successful and have been shown [2, 3, 4] to produce high false-alarm rates. Some contributing factors which inhibit the detection and classification are the diverse sizes and compositions of targets, variation of soil properties with location and moisture conditions, non repeatability of the target signature, competing clutter objects having similar responses as the actual targets, and partially obscured targets. In addition, the conventional target classification schemes lose their accuracy when the feature space is of high dimension and the classes cannot easily be separated. The later scenario typically occurs when multiple targets are present in the scene and their distribution functions or feature sets are overlapping with those of the non target anomalies.

Neural networks have been shown to offer potentially powerful, robust, and adaptive means of detecting and classifying targets under changing (or even new) signature and environmental conditions [5]. In this paper a new kind of network structure for the processing of minefield data is presented. This architecture consists of Self Organizing Memories (SOMs) and Backpropagation nets combined with the inter-neural WHU-Structures, whereby special pre-processing methods like DLS and fitting-methods are used to extract the feature specific items from the data in the minefield. This approach uses data from a small calibrated area to train the corresponding neural network, which is then used for mine detection over much larger areas.

Our experimental evaluation, using available sensory data [4] shows that the trained network architecture can be effectively used in areas which are geographically remote from the calibration area. The minefield data we use in the present study is based on measurements provided by ISPRA [4], with two different electromagnetic induction sensor systems, at a variety of geographic locations. These locations are denoted as Points, which is meaning that we have pre knowledge of the position. One source of inaccuracy in the practical use of the data we employ is related to the exact location of the sensor being used as data was registered. This is due to a variety of instrumentation and data collection effects, leading to errors in registering the sensor's position as it travels continuously across the minefield.

The key features of the proposed approach are the ability to adapt a user system to the metal detector/classifier network. This system and its constituent subsystems are introduced in the next section.

2. Time domain metal detector basics

Electromagnetic induction devices (Metal Detectors) are active, low frequency inductive systems. They contain one or sometimes several coils in their search head. The coil is carrying a electric current $I_{prim}(t)$ to generate a primary magnetic field $B_{prim}(t)$ that spreads through the ground. If it hits any metallic object, it reacts with the electric and magnetic properties of the target by inducing eddy currents $J_{eddy}(t)$, mostly circulating on the surface of the metallic object, also known as “skin effect”, and a secondary magnetic field $B_{sec}(t)$ is generated. Eddy currents emerge because of time-varying magnetic fields, primarily governed by Faraday’s Law of induction. The secondary field links back into the receiver coil in the search head, where an electric field $I_{sec}(t)$ is induced and converted into an audio signal. The secondary field $B_{sec}(t)$ depends on many parameters, e.g. the object’s shape, size, permeability and conductivity, the distribution of the primary field $I_{prim}(t)$, and the presence of interfering background signals, which is in particular the ground itself.

Besides the frequency domain (or continuous wave) metal detector, which uses an alternating (almost sinusoidal) electric current $I_1(t)$ at a fixed frequency and amplitude, a commonly used type of metal detector in humanitarian mine sweeping tasks is the time domain metal (TDM) detector [10]. TDM detectors are passing pulses of current through their coil (with a typical repetition rate of the order of 1 kHz), and eddy currents are induced in nearby conductive objects. The exponential decay of the corresponding secondary field, which is slower than the primary one, is observed with time. In presence of metal the generated magnetic field breaks down slower than in absence of metallic parts [3]. Figure 1) shows the schematic shapes of the time dependent behavior of the received magnetic field in different cases. In practice the signal is distorted with noise and the available information content of the decay parameters proposed in theoretical studies could not have been verified yet [5, 9, 11]. Hence in common TDM detectors an integration window to control the volume of the acoustic alarm signal is used (see Figure 2). For a more detailed description of electromagnetic induction devices refer to [4, 5, 6, 7].

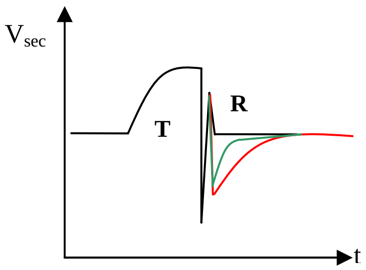

Figure 1. Schematic representation of the time-dependent decay of induced pulse with cases black: no metal, red: good and green: poor conductor. T denotes the transmission phase, R denotes the receiving phase.

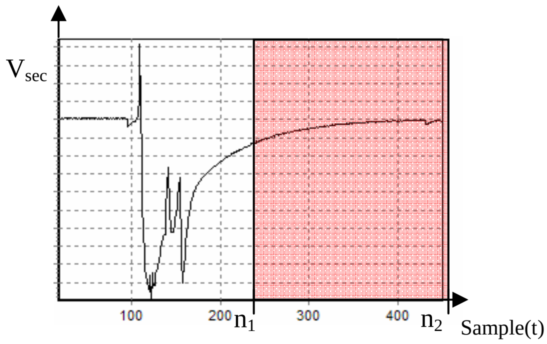

Figure 2. Example for the use of a fixed sized integration window to generate the accoustic signal to denote the metal content by a TDM detector (shown is a real signal received when moving the sensor head over a mine with “high” metal content).

3. Computing with activities

As on a closed grid every neuron has the same number of neighbours, the resulting activity pattern of the map shows symmetrical forms and no information stored in the neighbourhood of a classification concept will be lost because the representative neuron of the concept is placed at the margin of the Self organizing Map (SOM) [8]. This fact is most important for all kinds of steering and ruling systems with involved time trajectories as now a consistent continuation of a trajectory to all directions is guaranteed. Of course the region of the winner neuron (and the winner neuron itself) represents the scene globally but the detailed aspects of the classified scene are coded in the global activity pattern of the SOM. If the situation changes slightly, obviously the coordinates of the winner region will not change, but the oddment of the activity pattern will be modified. That means that only if the situations – coded by the common SOM learning strategies – change, the winner region will move accordingly. If only inferior situation aspects change, the winner region keeps its position. If the situation totally changes, the general form of the activity will change accordingly, whereby the ‘global state dynamics’ can be detected by the flux of the winner region, which is marked by the arrow in Figure 3. Based on these examples it should be clear, that the principle of the ‘Computing with Activities’ enables the continuous supervision of the real-time behaviour of a system [16].

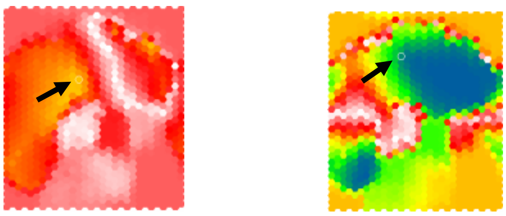

Figure 3. Activity structure of the SOM representing a different buried object situation. Right, a bullet (5 cm depth) in the sand and links Cola dose (10 cm depth)

3.1 Theory of the Whu-Structures

Even if the method of ‘Computing with Activities’ demonstrates totally new aspects for the supervision of complex systems; it will be more convenient if sub-patterns of high relevance can be extracted from the global activity pattern. This can be done by using two different kinds of ‘post-processing strategies’. The first of them defines a bias function, which emphasizes the neurons with the largest activities. Applying the second method however, a new structure on the neuron grid has to be defined, which enables a kind of 'situation relevant interaction' between the neurons of interest. In our experiments we tried both methods and detected that the first one is not an adequate way to deal with 'activities of higher interest' as the postulated bias function has to be case-related or recalculated from classification step to classification step.

Indeed the second way to emphasize the activity pattern of interest works more convenient and -as we have to learn from neurology- is closer to the principal of how brain works. For that reason we define a new kind of 'activity -oriented' neighbourhood on the SOM called 'wide hook up'-structure (resp. Whu-structure). The resulting net is more or less a SOM with an arbitrary activity-oriented neighbourhood function, which simulates an involved memory structure. Basic assumptions of this Whu-structure are presented in [15].

4. Proposed hybrid system

Our operator sequence to classify and detect predetermined objects consists of four sequential working modules. First, a smoothing of the analyzed raw signal is needed, which that part of the raw signal is belonging to the default integration window in the receiving phase. Raw data are always scattered with noise, mainly caused by technical perturbations and extern fluctuations due to the soils characteristic. This first module works as a pre-processing stage to obtain optimal input vectors for the neural classificators, as described below. Because of performance issues and the comparatively small random noise, a standard local averaging algorithm is applied: Let n_1 denote the number of that sample defining the left border and n_2 denote the number of sample defining the right border of the integration window outlined in Figure 2. If $v(n,p)$ denotes the received voltage $V_{sec}=(v(n_1,p),\ldots,v(n_2,p))$ at (the time dependent) sample n with p the two-dimensional position of the sensor head in a reference coordinate system and $\delta<(n_2-n_1)$ the diameter of the local average operator, the corresponding smoothed signal $v_s(n,p)$ is calculated as follows:

$$v_s(n,p)=\frac{1}{\varepsilon}\sum_{k=\left(n-\frac{\delta}{2}\right)}^{\left(n+\frac{\delta}{2}\right)} v(k,p), \quad n=n_1,\ldots,n_2, \tag{1}$$

with $(n)=n_1$ if $m<n_1$, $(n)=n_2$ if $m>n_2$ and $(n)=n$ else .

That part of the information of the received data, which allows to discriminate different objects (as far as possible), can be found on the one hand in the time-dependent decay of the induced pulse, but on the other hand definitely also in the spatial shape of the signals when moving the search head over the object. For this reason our neural classificator consists of two sequential feedforward nets. The fact, that a priori knowledge is known, implies the application of a supervised learning scheme. The adaptation of a neural net with a Whu-structure will first handle all kinds of information at the same 'high level' and select the relevant (surviving) parts of the information after the evaluation of the necessary parts of the input patterns.

The first step is a data pre-processing stage where the signal is filtered. An obvious requirement for effective curve-fitting is to have a respectable signal-to-noise ratio. As fitting function a Cumulative Exponentially Modified Gaussian with 5 parameters (EMG (a,b,c,d,e)) is used as an input and which is defined as follows:

$$y=\frac{a}{2}\left[1+erf\left(\frac{x-b}{\sqrt{2c}}\right)-\left(\frac{d}{|d|}+erf\left(\frac{x-b}{\sqrt{2c}}-\frac{c}{\sqrt{2d}}\right)\right)\exp\left(\frac{c^2}{2d^2}+\frac{b-x}{d}\right)\right] \tag{2}$$

with $erf(.)$ is the "error function" encountered in integrating the normal distribution and $c>0, d\neq 0$.

The next phase performs a mapping of the measurement to features. The features are a set of parameters that can be used to discriminate between different objects. The number of features will determine the complexity of the classification algorithm [15]. The output of the training stage, depends on the used algorithm and it is in general the set of parameters describing the different classes, which is referred here as ‘reference library’. The last phase is the classification which uses features derived from measurements and parameters from the reference library to decide the membership of the tested signal [16].

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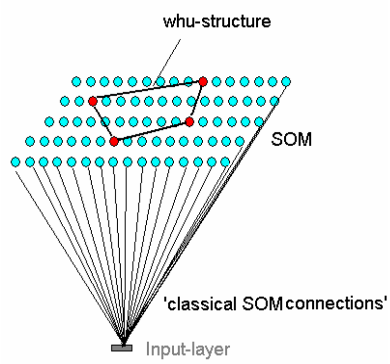

Figure 4. Schematic SOM with a Whu-structure

For the first experiments we chose a typical SOM enlarged by a Whu-structure as shown in Figure 4. it will be noted that normally one calculation step of such a structure is as follows:

- First the input pattern reaches the classical SOM structure and creates a global activity pattern.
- Now all neurons transmit their evoked activity through the interneuronal connections to the other neurons on the Whu-SOM.
- Next the algorithm scans which neurons form a ‘short cut component’ that is strong enough to maintain an activity pattern on the Whu-SOM.
- If the Whu-structure should be trained, these short cut weights are reinforced.

It is important to mention, that until now the aspect integration done by a Whu-structure has to be trained. This training is done by modifying the classical connections of a closed SOM (input layer $\rightarrow$ SOM) in a first training phase. Then the lateral connections are installed whereat a classical Hebb learning strategy is used.

The adaptation of a neural net with a Whu-structure will first handle all kinds of information at the same ‘high level’ and select the relevant (surviving) parts of the information after the evaluation of the necessary parts of the input patterns.

As shown in Figure 5, using metal detector different objects could be localized and detected in different depths and different soils. The raw signal will contain a significant number of features designed specifically to prevent the kind of errors that are common to curve-fitting. The greatest pitfall is probably using invalid data that consist either of erroneous values or some form of noise.

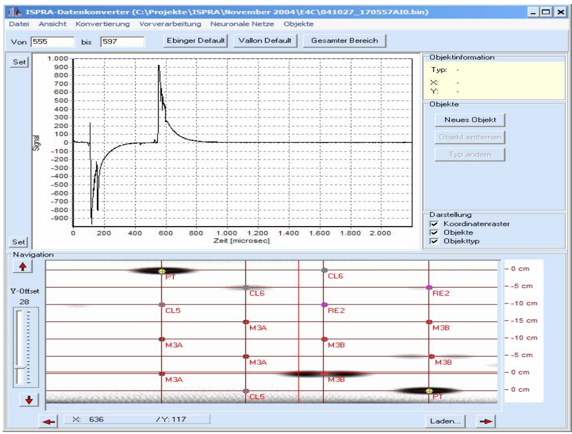

Figure 5. User interface of the buried object detection.

Accordingly the second stage of the supporting system is composed of a backpropagation net trained with different smoothed sample decay curves with the object of categorizing different quantatities of response signals. After a successful training phase the classification results obtained by propagating a smoothed decay curve v_s are given as follows:

$$BPP^{(1)}(v_s(n_1,p),v_s(n_1+1,p),\ldots,v_s(n_2,p)) \mapsto \left(\psi_1^{(1)}(p),\psi_2^{(1)}(p),\ldots,\psi_{o^{(1)}}^{(1)}(p)\right) =: \vec{\psi}^{(1)}(p) \in (0,1)^{o^{(1)}}, \tag{3}$$

with $BPP^{(1)}$ the classification mapping evaluated by the neural net via the training process. $o^{(1)}$ denotes the number of output neurons and equals the number of training vectors (decay curves). We considered that the combination of three different sample signals denoting no, low and high metal content is sufficient to categorize different (position independent) response signals, so just three output neurons are enclosed in this first stage of the neural classificator: $o^{(1)}:=3$. As the transfer function we use the standard sigmoidal logistic function $f_{act}(x)=(1+exp(-x))^{-1}$ for all neurons. Consequently for training the decay curve of no metal content is mapped to the desired output $\psi^{(1)}=(1,0,0)$, of low metal content to $(0,1,0)$ and of high metal content to $(0,0,1)$.

The output activities of the first backpropgation net are accumulated to a new spatial input vector while moving the sensor head over the examined slice of ground [12]. These spatial vectors work as inputs for the system's third stage, which is another feedforward net in order to classify the spatial trend of the induced voltage signals. Assuming a fixed number of the to be discriminated objects[1] N, a fixed maximum number of sample curves $w(N)$ defined by the maximum elongation of the N objects and a uniform motion[2] of the sensor head from positions p_1 to $p_{w(N)}$ defining the vector of movement $\vec{p}$, the second backpropagation net performs the transformation

$$BPP^{(2)}\left(\vec{\psi}^{(1)}(p_1),\vec{\psi}^{(1)}(p_2),\ldots,\vec{\psi}^{(1)}\left(p_{w(N)}\right)\right) \mapsto \left(\psi_1^{(2)}(\vec{p}),\psi_2^{(2)}(\vec{p}),\ldots,\psi_N^{(2)}(\vec{p})\right) =: \vec{\psi}^{(2)}(\vec{p}) \in (0,1)^N, \tag{4}$$

whereas the desired output activity $\vec{\psi}_{des}^{(2)}$ for each object $k \in \{1,2,\ldots,N\}$ is given by

$$\vec{\psi}_{des}^{(2)}\left(\vec{p}^{(k)}\right) := \left(0,\ldots,0,\underbrace{1}_{k-th\ component},0,\ldots,0\right). \tag{5}$$

[1] If an object should be detected in different depth stages, each stage has to be defined as a single object.
[2] A uniform motion is possible only if using a robot. The use of the detector by a human deminer requires an exact position acquisition and an algorithm to transform the data into a suitable format.

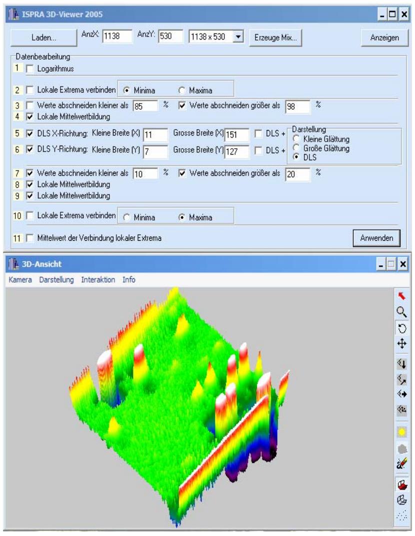

Figure 6. Screenshot of the user-interface of the postprocessing and 3D-imaging system.

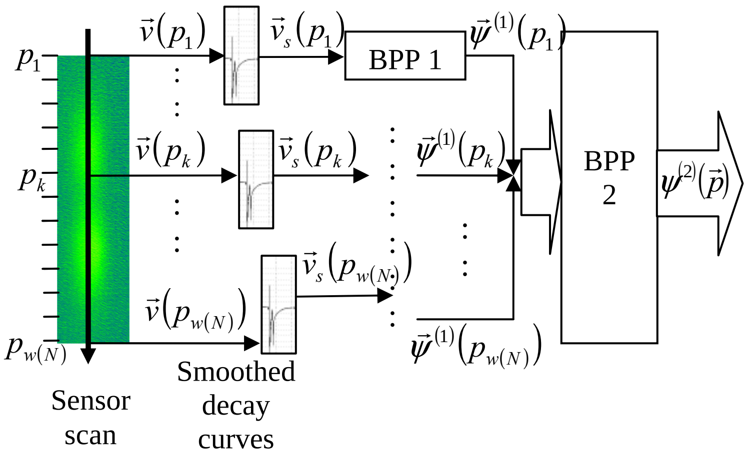

Figure 7. Schematic overview of the processing mode of the supporting system

Considering the dimension of the input vectors of the second net, the usage of the first net to categorize the decay curves now becomes clear. The number of samples of a default integration window averages about 50 samples, dependent on the sample rate. If using just one net and assuming about 100 decay curves (sensor positions) to successfully categorize the spatial gradients, the number of input neurons of single net results to ~5000 neurons. The task of the first categorizer is to compress the information stored in the decay curves in an automatic manner and thus to save input neurons of the spatial classifier and to increase performance, both in training mode and execution mode.

The last module of the supporting system acts as a postprocessor and consists of different smoothing and visualizing routines, e.g. a 3D-imaging system (Figure 6), spatial smoothing routines both in x- and y-direction, scale- and zoom-operators, etc., that can be manually switched on or off by the deminer to deal with different soils and environmental conditions. Because the images of the just pre- and post processed data are more suitable for detecting objects quickly ("first review"), the neural nets may be switched off by the deminer. After the detection of different potential mines, the neural classificator is switched on in order to facilitate in classifying the objects. Figure 7 shows a schematic overview of the supporting system.

For evaluation purpose we used real data measured at the European Joint Research Centre test site in Ispra, Italy. The descriptions of the mine fields, measurement conditions and additional data are available online [14]. We used the measurements of field 4C, whose soil consists of pure sand, to condition our supporting system. Figure 8 shows the results after successful training with six objects (mine surrogates of type "M3B" buried in depths 0cm, 5cm, 10cm and 15cm, high metal content reference object on the surface and one pure soil measurement). We trained the second backpropagation net with a maximum width of *w(N)*=120 sample curves, resulting in 360 input neurons of the second net. The activities of the output neurons $\psi_1^{(2)}(\vec{p}), \psi_2^{(2)}(\vec{p}), \ldots, \psi_6^{(2)}(\vec{p})$ have been calculated, postprocessed and visualized with the proposed supporting system (Figure 8). In the first picture the correct classification of the mine on the surface, or better its signature, is obvious. Though neuron 2, which is responsible for the classification of the mine buried in 5cm depth, correctly indicates the correct position of the mine, it misleadingly recognizes another object (bullet cartridge, in the center of the upper part of the field) as a mine. This misclassification must be cleared out by comparing the activities of other output neurons at the positions of both objects. For example, the comparison of the results of neuron 3 points out the difference of both objects. This does apply to neurons 3 and 5, too. The worst case, which is the mine in 15cm depth, cannot be resolved by our supporting system. However the high activities close by the relevant position should be taken by the deminer as an indicator for an increased probability of the presence of a mine being searched for.

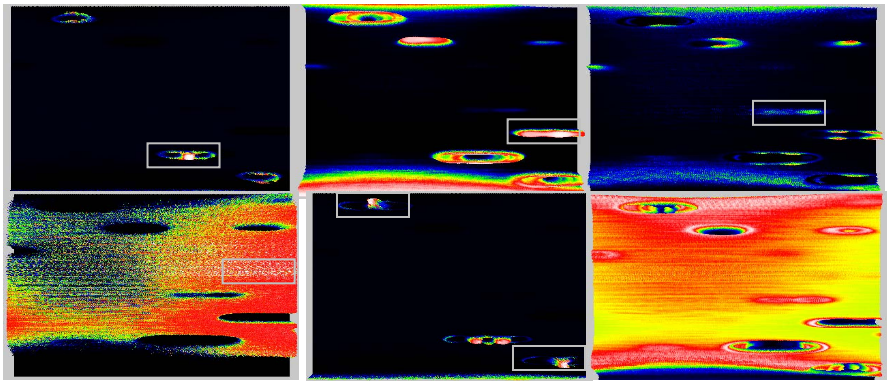

Figure 8. Color-coded activities of the six output neurons of a trained network when using data of the JRC test site, Ispra, field 4C. Displayed are the activities at each position of the analyzed area (size: 6m×2m) of the output neuron trained with signals of (from upper left to lower right) mine on surface, in 5cm depth, in 10cm depth, in 15cm depth, high metal content reference object, sample ground signal. Gray frames denote the real positions (see [12, 13]) of corresponding objects.

The first results illustrated for one example measurement indicates the ability to partially discriminate different objects, if the deminer has been trained to interpret the graphically represented activities of the net's output neurons. Comparable results have been achieved with other soils and training objects.

5. Conclusions

A combined neural supporting system to help the operator determining the type and depth of buried objects when using a standard time domain metal detector is proposed. First analysis of the obtained results denotes the possible decrease in false alarm rates.
An efficient approach to localise and to detect buried objects using metal detector is presented. The algorithm can eliminate the distracting influence from soils and can detect metal objects in different depths.

The quality of the obtained results is based on the assumption that the objects to be found (anti-personell mines) are known a priori to gather appropriate training vectors. This requirement is fulfilled in the majority of cases in humanitarian demining tasks. The collection process of suitable training vectors can be done on field and/or by access of a database. The online gathering has the advantage of adapting to existing environmental conditions like temperature, soil moisture etc.

While our approach showed satisfying results with the provided sensorial data from the JRC test site, it must be pointed out that the system will be analyzed this summer with a test campaign in Croatia, where a deminer will collect the data instead of using a robot. This will result in nonlinear movement, what has to be compensated by additional routines to calculate as exact as possible the real position of the sensor head for each sample. Furthermore sample signatures of rotated objects have to be surveyed and analyzed.

References

[1] Proceedings of the Discussion Day on Soil Electromagnetic Characteristics and Metal Detector Performance, EU-JRC,ISPRA,http://www.itep.ws/whatsnew/121202/soil.html.

[2] Ping Gao, L. Collins, P.M. Garber, N. Geng, and L. Carin, “Classification of Landmine-Like Metal Targets Using Wideband Electromagnetic Induction”, IEEE Transactions on Geosciences and Remote Sensing, Vol. 38, pp. 1352-1361, 2000.

[3] S. L. Tantum, and L. M. Collins, “A Comparison of Algorithms for Subsurface Target Detection and Identification Using Time-Domain Electromagnetic Data”, IEEE Transactions on Geoscience and RemoteSensing, Vol. 39, pp. 1299-1306, 2000.

[4] T. Doi, and G. Plett, “Adaptive Neural Networks for Mine Detection”, Technical report for contract DAAK70-92-K-0003, Stanford University, 1995.

[5] M. Draper, and T. Kocak, “Performance of EMI Based Mine Detection using Back-Propagation Neural Networks ”, ESANN'2005 proceedings - European Symposium on Artificial Neural Networks Bruges, ISBN 2-930307-05-6, 2005.

[6] J.C. Alldred, “The Pulse-Induction Principle”, Protovale Oxford Ltd., Tech. Note T-41, 1992

[7] C. Bruschini, “A Multidisciplinary Analysis of Frequency Domain Detectors for Humanitarian Demining”, PhD Thesis, Vrije Universiteit Brussel, ISBN 3-89825-853-X, 2002

[8] L. Collins, P. Gao, L. Carin, “An Improved Bayesian Decision Theoretic Approach for Land Mine Detection”, IEEE Trans. Geoscience and Remote Sensing, Vol. 37, No. 2. , 1998

[9] International Campaign to Ban Landmines, “Landmine Monitor Report 2005 – Toward a Mine-Free World”, Human Rights Watch I, ISBN 0-9738955-0-0, 2005

[10] Rae McGrath, “Landmines and Unexploded Ordnance – A Resource Book”, Pluto Press, ISBN 0-7453-1259-4, 2000

[11] C.V. Nelson, et al., “Wide Bandwidth Time-Domain Electromagnetic Sensor for Metal Target Classification”, IEEE Trans. on Geoscience and Remote Sensing, vol. 39, no. 6, pp. 1129-1138, 2001

[12] P.J. Werbos, “Backpropagation through time: what it does and how to do it.”, Proceedings of the IEEE, 78(10), pp. 1550-1560, 1990

[13] A. M. Lewis, et. al., “Multisensor Mine Signatures”, Final Report of ITEP Project 2.5.1.2, http://demining.jrc.it/msms/MsmsFinalReport.pdf, 2004

[14] Eudem 2: EU projects, http://www.eudem.vub.ac.be/projects/.

[15] H.H. Tadjine, and M. Reuter, “Computing with Activities III: Chunking and Aspect Integration of Complex Situations by a New Kind of Kohonen map with whu-structures (Whu-SOMs)” , Proceedings of the IFSA 2005 World Congress, Fuzzy logic, soft computing and Computational Intelligence Theories and Applications, July 28-31, Beijing, China, Springer Press, 2005.

[16] M. Reuter, “Computing with Activities”, LNCS 2206, Springer, Heidelberg, pp. 174-184, 2001.