New Signal Processing For Metal Detectors in the Humanitarian Mine Clearance

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Abstract. Today for clearing areas from landmines, beside dogs and searching needles, almost excluding metal detectors are used. Available metal detectors, specialised for mine clearance, are high sensitive also on small metal parts. Nevertheless, they give no further information about the buried object (depth, size, shape, material). Besides, the high false alarm rate of the hand-held detectors makes the mine clearance a protracted and cost-intensive process. Reasons for the high false alarm rate (up to 1000 false alarms per mine) are “uncooperative” soils, harmless metallic objects like shell splinters, but also the low metal content in newer anti-personnel mines.

By the evaluation of multivariate local referenced sensor data, a reduction of the false alarm rate will be reached (soil compensation, classification). In cases of using a-priori information (types of mines in the field are known) it is possible to use a database with mine signatures from different depths for an automatic object classification.

A special advantage of the procedure described here, is that an estimation of the detection probability of a certain mine in the present soil with help of a simple ground measurement using the metal detector is possible. Therefore the mine-to-soil-signal ratio can be determined in the field for every mine in every depth (available in the database) and gives a good approximation of the maximum detection depth.

Introduction

Metal detectors used for anti personal landmine clearance are based on the eddy current principle (with use of impulse-, single- or multi- frequency excitation). The state of the art is to convert the received signals into an acoustic signal, which gives the user a clear indication for the presence of a metallic object. Determining the two-dimensional positions (pinpointing) is easily possible for a qualified deminer, however a sure classification of the object properties (depth, size, shape and material) is almost impossible. Such classification features are provided by some detectors for treasure hunting [12]. But the methods used there, are not reliable in the case of small composite metal parts of different material and complex shape, mines usually consist of. Also the influence of uncooperative soil is almost neglected by object classification methods.

The joint Project HuMin/MD (www.humin-md.de) is founded by the German Federal Ministry of Education and Research (BMBF) and consists of 12 Institutions (mainly Universities and Fraunhofer Institutions). The aim of this project is the investigation of new methods to reduce the high false alarm rate of standard metal detectors.

The working group from Rostock provides synthetic and measured data of different metal detectors as a service to the whole joint project. The research activity follows two approaches. The first is the visualisation that gives the deminer additional information about the geometrical distribution of the metal parts and the second approach solve the
problem of the high false alarm rate by processing of multi parameter sensor data and usage of a priori information (type of mines in the field) for a database supported object classification.

1. Visualisation of local-distributed sensor data

1.1 Acquisition of sensor data

For the visualisation of sensor data, the measured values can be acquired under lab terms with help of a 2-axis-scanner on an equidistant two dimensional grid (Fig. 1). The measuring data can be visualized as raw-data (Footprint - Fig. 2), reconstructed picture (deconvolution - Fig. 3) or phase loops in the complex plane (Fig. 8).

Nevertheless, a hand-controlled system requires a lightweight and contactless working high-resolution position sensor. Available differential GPS solutions are only usable for seeking unexploded ordnance (UXO). They are difficult to handle, expensive and not usable in every terrain (forests). Especially to acquire the signature of an anti-personnel mine with a high spatial resolution, needed by further signal processing methods, the accuracy of such systems is too low. To resolve this problem, a special optical position sensing system, based on spatial filtering techniques, could be used [8] [9].

![Fig. 1. Different metal detectors (three left), two-axis-scanner (right)](image)

1.2 Image reconstruction, using the deconvolution method

In the case where the size of the sensor element, e.g. differential eddy current core coil, is larger than the size of the inhomogeneity, the sensor signal is also dependent on the aperture size of the sensor element. In general the measured sensor signal $S(x,y)$, e.g. the magnetic field distribution $B(x,y)$, can be calculated by convolving the aperture of the sensor $AS(x,y)$ and the aperture of the defect (if $z = \text{const.}$). The use of an absolute instead of a differential probe generates different sensor signal patterns [1].
Fig. 2. Three balls, aluminium, copper and steel, diameter 28 mm: Raw ‘eddy current images’ (real and imaginary part)

Fig. 2 shows the raw ‘eddy current images’ (real and imaginary part of the complex secondary coil voltage) from a scan over three metal balls of aluminium, copper and steel (diameter 28 mm, 5 cm centre distance) placed 5 cm under a sensor coil. Because of the strong blurring, caused by the wide sensor aperture function, the three objects can’t be separated in the raw-data images.

The objects are clearly separated in the reconstructed image, shown in Fig. 3, that is the result from the deconvolution of the sensor signal $S(x,y)$ with the sensor aperture function $AS(x,y)$ [7].

Visualising also the phase from the deconvolved raw-data-components, allows the separation of iron- and non-iron-metal parts, which gives additional important information to characterise the object.

As a further example, Fig. 4 shows the ability of reconstructing the shape of a metallic object.

Fig. 4. Bended wire (le.) in 25 mm depth, raw-data (mid.) acquired with a commercial metaldektektor, raw-data (left), reconstructed image (ri.)
Deconvolution methods are not restricted to the continuous wave principle. Fig. 5 shows the image reconstruction of three metal balls using a pulse-induction metal detector with an absolute coil.

![Image of three balls, aluminium, copper and steel, diameter 28 mm: reconstruction – raw-data (left), sensor aperture function (middle) and the reconstructed image (right)](image)

The deconvolution is very sensitive against noise, so it is restricted to objects near the surface and/or with a high metal content. The need of exactly position referenced measurement data can be achieved with an automated two-axis scanning system or a sensor array but makes it not applicable for today’s handheld metal detectors. Therefore an optical position reference system, based on spatial filtering, is used.

### 1.3 Manual 2D-Data acquisition

The basic idea of spatial filtering velocimetry is to observe the optical image of a moving object through a set of parallel slits. Due to the narrow band pass filtering of the slits the output signal $u(t)$ of the photo detector contains a frequency $f$ related to the object velocity $v_x$. By integration of the $v_x$ we can use the spatial filtering sensor as a position sensor. Instead of the commonly used transmission grating, in our approach, structured detectors such as CCD (charge coupled device) and CMOS sensors are acting both as detector and as spatial filter. These imagers ensure the required high precision of the gratings and enable a compact measuring system [8][9]. As a cost-effective and light weight version also a webcam can be used [14], which can be mounted on a handheld metal detector (Fig. 6).

![Construction example of a metal detector with an optical position sensor and a PDA for data acquisition and visualisation](image)
There is a dramatically decrease of detection probability in soils with magnetic properties \((\mu_r>1)\) or inhomogeneous conductivity because of the dominant ground signal, especially in terms of mines with low metal-content. If the detector provides \(n\) linear independent parameter, it is well known from eddy current testing, that up to \(n-1\) parameter can be used to suppress \(n-1\) disturbance values.

Today’s metal detectors mostly provide ground compensation functionality. But the probability of detection (POD) still decreases in comparison to so-called “cooperative” soils (e.g. sandy soil). The more similarly ground- and mine-signals are, the more ground compensation reduces the mine signal also. Up to now, an approximation of maximum detection depth of a certain mine in uncooperative soil is not possible for the deminer.

This problem can be solved with a database of mine signatures (which were measured under lab-conditions) and the position referenced data acquisition. The database contains the signatures of all mines which are expected in the field (a priori information) in several depths. At first a segment, which is free from metal, must be scanned in the field. Afterwards the algorithms of the ground compensation are applied separately to the ground measuring data and the mine signatures from the database (lab measurement in air) (Fig. 9, on the left).

Therefore the mine- to soil-signal ratio can be determined on site for every mine in every depth and gives a good approximation of the maximum detection depth.

The ground compensation algorithms from the available metal detectors minimise the soil-signal without a look to the different target object signatures. By using a signature database it is possible, to maximise the target to disturbance signal level instead of only minimising the soil effect for itself.

Furthermore, the soil compensation algorithms have to be slightly different for visualisation and classification purpose. For classification, we have to take a compromise between the best possible soil compensation and the number of parameter left for feature extraction. To visualise measurement data in a 2-D-intensity plot or just give an audio signal to indicate a suspicious object, all input values can be combined to only one output value with the maximum of target to disturbance signal ratio.

Fig. 7 shows the measured raw-data of a mine in a strongly uncooperative laterite soil (left four), where only the soil inhomogeneities can be seen and the result of soil suppression (right).

In comparison to the audio signal, used up to now, the on-line visualisation of position-referenced measured data allows an easier localisation of the signature, especially in situations with a low signal to noise ratio. Therefore, as shown in Fig. 7 for a continuous wave detector, but also valid for pulse inducting detectors, raw-data pre-processing with ground compensation algorithms is essential.
The on-line visualisation shows to the deminer also, if the signature is already completely and accurate scanned. That is important for the automatic classification described in the next paragraph.

2. Object classification with use of phase plot features

The representation of object signatures in the complex plane (phase loop representation) is advantageous because the requirements for the accuracy of the sampling grid and the signal to noise ratio are much lower in comparison to e.g. deconvolution methods [5][6]. There will be no exact picture from the distribution of the metallic parts, but a signature that is typical for the material, form and position of them (Fig. 8). The phase loop representation is a known procedure in eddy current testing [3], an adaptation to mine detection is described in [4] and [5].

![Fig. 8. Signatures of: mine, bullet cartridge and aluminum can and a steal ball](image)

Nevertheless, to meet a decision with the help of the signature demands a lot of experience from the deminer. Hence, the information content of these representations is to be condensed by suitable algorithms (feature extraction) [10] [11].

The mostly known variance of different mines faces a nearly boundless number of possible clutter objects in the field. Therefore, as a database for a classification, only the features of the mine signatures are sensible. favouring above others comes that to the deminer is often known which mine types (often not more than two) are present in an area. Those signatures which differ clearly from them of mines can be interpreted as false alarms.

![Fig. 9. Signal processing (purpose: dependability, mine recognition, visualisation)](image)

Nevertheless, the mine signatures are strongly distorted by the soil influence with increasing depth. The upper line of Fig. 10 shows two phase-loops per plot, which
represents the real vs. the imaginary part of the complex coil voltage for two frequencies (2.4 and 19.2 kHz). Because of the dominating soil influence in the imaginary parts, sensor raw-data are not directly usable for the feature extraction in the presence of uncooperative soil. Hence, soil compensation (as described further above) is applied to the measured data before feature extraction. To guarantee the comparability of measurement and database, it is necessary that the signatures from the database pass the same algorithms (Fig. 9, centre).

Fig. 10. Signatures of a mine in different depths raw-data (top) and with ground compensation (bottom)

For a classification, amplitude, phase or geometrical features from the phase loop can be used. Last one is promising only for objects what gives a strong signal. But with the aim to classify also small and/or deep lying objects (low signal to noise ratio) phase and amplitude are the more stable features.

Fig. 11. Test lane from JRC Ispra [13]

Tests with measurements taken, on the test lane from the Joint Research Centre in Ispra (Italy) [13], with a commercial two-frequency metal detector show, that most clutter can be divided from mines with a sufficient metal content with use of only two features. Problematic are mines with a low metal content because they give a weak detector signal, which is already near the noise level below 5 cm depth. That can be slightly improved by spatial averaging (multiple detector movements over the same area) and shows the need of further optimisations on detector design with the view to classification and visualisation ability.

An important condition for a reliable object recognition using the procedure described here is, that the direct surrounding of the mine is free from other metal parts. In particular bigger metal parts can conceal the signature of a neighbouring mine. Thus, the distance between a
clutter object and a mine must be larger than approximately the double searching coil diameter.

3. Conclusion

A main problem of mine clearance is the high false alarm rate, which is caused primarily by soil inhomogeneities and harmless metal parts (clutter).

By the evaluation of multivariate local referenced sensor data, a reduction of the false alarm rate is possible (soil compensation, classification). Especially with a priori information about the mine types in the field a clear lowering of the false alarm rate can be reached. The database necessary for this is generated by lab measurements (2D-scans of mines in air). A method using also synthetic data from a fast forward simulation is currently under investigation and could be used for a fast adaptation (depth, orientation) of the mine signatures in the database.

An additional advantage of the procedure described here, is that an estimation of the detection property of a certain mine in the present soil with help of a simple ground measurement using the metal detector is possible.

References