A Simple Metal Detector Model to Predict the Probability of Detection in Landmine Detection

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The modelling

- Modelling the metal detector
- Modelling the effect of the soil
- Modelling the height of the coils over the ground
- Modelling the measurement errors
- Modelling the operator

Evaluation

- The data
- A basis for comparison: the generalised linear model
- Method of evaluation

Results

- Maximum likelihood
- Reducing the number of parameters
- 95%-confidence intervals

Discussion and further work

Objectives

Goal Design and evaluate a model for a metal detector used in the context of humanitarian mine action

Motivation Predict the performance of metal detectors in a given situation, support T&E by helping the design of trials with less measurements needed to evaluate the probability of detection as a function of depth, etc.

Method Model the working principles of a metal detector, the effect of the soils, the operator

When estimating the probability of detection, a bias can occur if the model is wrong. It is therefore important to evaluate the model.

Modelling the metal detector

- Assume that there is an alarm indication if the response produced by a given target is higher than a threshold set during the set-up or calibration phase of the metal detector
- The response produced by a given target (a small metal ball) in the receiving coil is $V = k.H_{RX}.H_{TX}$ where H_{RX} and H_{RX} are the magnetic fields produced in the transmitting and receiving coils respectively; k is a constant (which can be set to 1 without loss of generality).

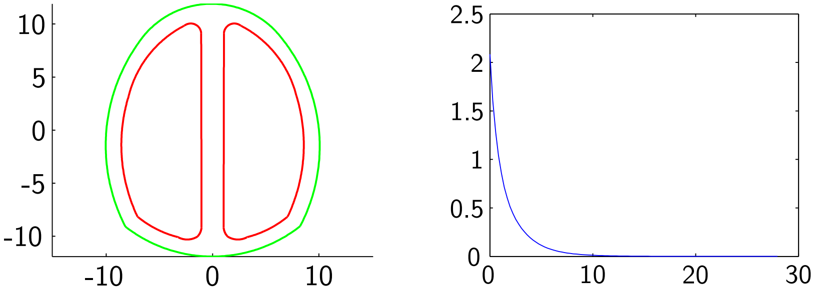
First parameter: the threshold

The metal detectors used

The Minelab F1A4 (left), the Foerster MINEX 2FD 4.530 (top) and the Minelab F3 are used.

(Image source: JRC/EC)

Example of modelling Foerster MINEX 2FD 4.530



Left: the modelling of the coils; Right: the curve of the target signal as a function of distance to coils (depth in centimetre). The target is modelled as a small metal ball.

Modelling of the effect of the soil

- Assume that the soil adds a Gaussian noise to the target response of the metal detector.
- The mean of the Gaussian noise can be assumed to be zero by shifting the value of the threshold.

Second parameter: the standard deviation of the soil noise

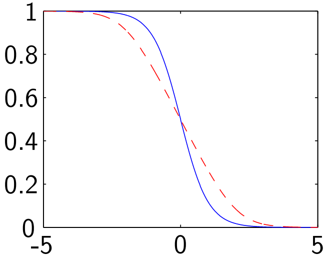
Modelling the height of the coils over the ground

- Following CWA 14747-1, the depths of buried targets are measured from the surface of the ground to the top of the target.
- The metal detector is swept at some (variable) distance from the soil surface.
- Hence the need to have the height at which the detector is swept over the soil surface as an additional parameter.
- This parameter also accounts for the fact that the metal parts of a true target may not be located exactly at the top of the target.

Third parameter: height of the detector over the soil surface

Modelling the measurement errors

- Measurements of distances may have errors: Approximative depth measurements; variations of coil height, irregular soil surface
- Assume a uniform distribution centred at 0 for the depth errors



Introducing depth errors leads to a convolution of the probability of detection as a function of depth by the distribution's support

Fourth parameter: half-width of length of the distribution's support

Modelling the operator

The operator may:

- miss a target although the metal detector generated an alarm indication (false negative)
- declare a detection although the metal detector did not generate an alarm indication – even if a target is present

Fifth parameter: probability that the operator misses a target
Sixth parameter: probability that the operator wrongly detects a target that the metal detector did not.

The data

STEMD Laboratory tests Systematic Test & Evaluation of Metal Detectors (STEMD) Laboratory Tests Italy: tests performed at Joint Research Centre (Ispra): provides information on the working principles of many metal detectors (see also catalogue from Geneva International Centre for Humanitarian Demining)

STEMD Croatia Systematic Test & Evaluation of Metal Detectors (STEMD) South-East Europe, Croatia: provides data of mine detection as a function of depth with various metal detectors, operators, soils, targets

Mines used

PMA-2

PMA-3

(Image source: ORDATA)

A basis for comparison: the generalised linear model

- The model was introduced by Prof. Wilrich and BAM (Germany) to analyse the data from the STEMD trials.
- The purpose of the model is to provide a simple way to estimate the probability of detection as a function of depth.
- The probability is modelled as a logistic function with two parameters:

$$p(x) = \frac{1}{1 + e^{ax+b}}$$

where x is the depth, and a and b are the two parameters of the model

Method

- Parameter optimization is used to fit the generalised linear model and the physical model for each data set (one metal detector, one soil, one operator, one target) by maximizing the likelihood (probability to have the data set given the model).
- The values are compared for each data set, for each soil and for each metal detector.
- A small study on the relative importance of the six parameters has been performed.
- 95%-confidence intervals have been estimated.

Maximum likelihood

Using three metal detectors, three soils (Obrovac, Sisak and Benkovac) and two targets (70 data sets)
Assuming that these two models are the only ones possible and have the same prior probability, the probability p_{right} that the physical model is the right one is equal to:

- $p_{right} = 0.56$ given each data set (mean value)
- $p_{right} = 0.9975$ given all data
- $p_{right} = 0.9997$ given all Minelab F1A4 data
- $p_{right} = 0.9998$ given all Minelab F3 data
- $p_{right} = 0.9981$ given all Foerster MINEX 2FD 4.530 data
- $p_{right} = 0.9975$ given all Obrovac data
- $p_{right} = 0.9999$ given all Sisak data
- $p_{right} = 0.9995$ given all Benkovac data

Reducing the number of parameters

- On a few data sets, a preliminary study of the relative influence of the six parameters has been performed.
  1. Find the parameter that, when removed from the model, reduces the least the maximum likelihood.
  2. Remove this parameter.
  3. Find the next parameter that, when removed from the previous set of parameters, reduces the least the likelihood.
  4. Repeat until the maximum likelihood reduces too much.
- Removing the probability of generating a false alarm (and to a lesser extent the smoothing of the 'detection as a function of depth' profile of the metal detector) does not deteriote the quality of the physical model.

95%-confidence intervals

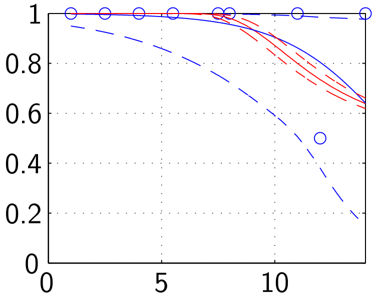
The 95%-confidence intervals for the curves giving the probability of detection as a function of depth have been estimated numerically:

1. Compute the likelihoods on a large sample of the parameter space.
2. Compute the global sum of all these likelihoods.
3. Compute and sort the cumulated sums.
4. Find the likelihood for which this sum is equal to 95% of the global sum.
5. Select the paramaters that generate a likelihood higher than the likelihood computed above.
6. Use the envelop of the curves for the selected parameters as bounds for the 95%-confidence intervals.

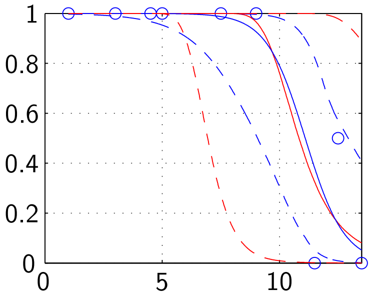
Example of 95%-confidence intervals

Minelab F3, Obrovac soil, $p_{right} = 0.56$

Blue: generalised linear model Red: physical model



One PMA-2 at each of 8 depths; plus two at 12 cm.



Two PMA-3s at each of the 9 depths

Discussion

- The physical model fits experimental data better than the generalised linear model.
- It has more parameters
- These parameters have a physical meaning and may contain valuable information (relative effects of metal detectors and operators, support for soil classification based on the standard deviation of the soil noise, etc.)
- The parameters of the two models are estimated with the same data used to compute the comparaisons. This may lead to overlearning for both models.

Further work

- Use an Neyman-Pearson hypothesis test on the physical model
- Test what happens if a wrong coil configuration is used in the model
- Improve the estimation of the 95%-confidence intervals
- Use a complete Bayesian approach (compare the two models for all parameters and not just for the optimal parameters)
- Use different data sets for learning and evaluation, or use a 'all but one' procedure to ensure that no overlearning occurs
- Improve the optimisation procedure
- Reduce the number of parameters
- Etc.