EFFECTS OF MAGNETIC SOILS ON MAGNETOMETRY IN UXO DISCRIMINATION PROBLEMS

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Abstract

Magnetometry has emerged as an effective tool for UXO discrimination. The current approach is based upon the magnetic dipole moment recovered from the inversion of surface total-field magnetic anomalies. However, the reliability of inversion will be strongly influenced by the noise in the data such as that produced by magnetic soils in the background geology. We examine this problem to understand under what conditions the magnetic dipole inversion will be severely affected and, when such conditions occur, how to alleviate the effect. We achieve this by evaluating the errors of the dipole inversion due to different soil susceptibilities. The magnetic susceptibility of soils is modeled as a correlated random process whose spectral property is estimated using the TEM data from Kaho’olawe, Hawaii. The UXO response is modeled as that of a dipole embedded in the soil. Inverting the total-field response using a large number of soil realizations yields a reliable estimate of the errors. To remove the soil effect, we propose to preprocess the data before applying inversion. We show that a Wiener optimal filter can be used as a preprocessing tool to alleviate the effect of the soil response and reduce the errors of inverted dipole parameters, thus providing better confidence in discrimination.

Introduction

Background

The two most effective geophysical techniques for UXO investigations are magnetic and electromagnetic surveys. These have a well-documented ability to locate UXO’s but are prone to excessive false alarms, which significantly increases the cost of clean up. For instance, at some sites up to 75% of excavated items are non-UXO. The key to reducing these false alarms is the development of algorithms that can discriminate between an intact UXO and other items such as scrap metal or geological features.

Recent developments have enabled the recovery of dipole or ellipsoidal parameters through inversion of magnetic data (Billings et al. 2002). Similarly, frequency and time-domain electromagnetic measurements can be inverted to recover parameters in reduced modelling formulations (Pasion and Oldenburg, 2001). These recovered parameters can be used to discriminate between UXO’s and other items. In magnetometry, for instance, the deviation of recovered dipole moment from the expected dipole moments induced in different UXO items by the earth’s field is used as a discrimination criterion.

The above inversion methodologies have been developed with the underlying assumption that the collected data result from objects buried in a non-magnetic background. In practice this is not always the case. At many sites (e.g. former Fort Ord; the former Naval range at Kaho’olawe, and Helena Valley, Montana) the soils are known to have significant magnetic susceptibilities. That background significantly modifies the measured magnetic or electromagnetic responses and thus adversely affects the performance of the existing inversion algorithms. This reduces our ability to discriminate and results in false alarms. For instance, approximately 60,000 anomalies were dug at Kaho’olawe site, and the false-alarm rate is about 32. Among the false anomalies, 27% were caused by geology. Therefore, it is
important that we understand the effect of magnetic soil on these two widely used techniques in UXO and develop approaches to mitigate such effect in order to improve the detection and discrimination capabilities. Pasion et al. (2002) have studied the effect of magnetic soil on electromagnetic data. Our study focuses on the effect on magnetometry.

Within this paper we determine how magnetic soils affect the recovered parameters from magnetic inversions and, if this effect is significant, to explore possible techniques to mitigate the effects. The specific objectives are:

1. Quantitatively evaluate the effects of the background susceptibility and thereby determine under what conditions magnetic inversion algorithms can work (while ignoring these effects),
2. Determine how the data can be modified so that the current inversion algorithm will work in the presence of background susceptibility.

We provide a brief background on the factors that affect the soil susceptibility and then study the response of soil magnetic susceptibility in static magnetic surveys, and assess the level of soil response that will severely affect the performance of current discrimination algorithms based on geophysical inversion.

**Soil Magnetic Susceptibility**

The magnetic properties of soils are mainly due to the presence of iron. Hydrated iron oxides such as muscovite, dolomite, lepidocrocite, and goethite are weakly paramagnetic, and play a minor role in determining the magnetic character of the soil. The magnetic character of the soil is dominated by the presence of ferromagnetic minerals such as maghaemite and magnetite. Maghaemite is considered the most important of the minerals within archaeological remote sensing circles (e.g., Scollar et al., 1990). Magnetite is the most magnetic of the iron oxides, and is the most important mineral when considering the effects of magnetic soils on total-field magnetic and EM measurements (Pasion et al., 2002). Given the presence of these magnetic minerals, the strength of the magnetic susceptibility primarily depends upon the mass fraction of the dominant magnetic minerals.

The static magnetic sensors are sensitive to the presence of magnetic minerals because the earth’s magnetic field creates an induced magnetization. The anomalous magnetic field produced by the soil magnetization will superimpose on the magnetic anomalies produced by UXO’s and other metallic objects and therefore introduce adverse effect in the discrimination problem.

**Table 1.** Magnetic susceptibilities of four samples collected at Seagull site on Kaho’olawe. The susceptibility is measured at two frequencies and the unit is $10^{-5}$ SI.

<table>
<thead>
<tr>
<th>Sample - depth</th>
<th>Frequency (0.46 kHz)</th>
<th>Frequency (4.6 kHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-6&quot;</td>
<td>3554</td>
<td>3344</td>
</tr>
<tr>
<td>A-24&quot;</td>
<td>3022</td>
<td>2771</td>
</tr>
<tr>
<td>AP-6&quot;</td>
<td>1726</td>
<td>1630</td>
</tr>
<tr>
<td>AP-18&quot;</td>
<td>1529</td>
<td>1448</td>
</tr>
</tbody>
</table>
The magnetic soil at Kaho’olawe site has been studied by other researchers and we cite the data here as examples. Kaho’olawe is a single volcanic dome made of thin-bedded pahoehoe and a’a basalt (Stearns, 1940). Base rock is tholeiitic basalt (Pasion et al., 2002) and it is covered by a number of different soil types with variable geophysical characteristics (Parsons-UXB, 1998). As an example, Table 1 lists the magnetic susceptibilities measured at a site on Kaho’olawe. The magnitude of the susceptibility value provides the basis for our simulation of soil response.

In the following, we investigate the effect of magnetic soil on static magnetic measurements by simulated magnetic soil using correlated random susceptibility distributions and quantify the errors it introduces to the inversion. We then show a method to remove the soil response before applying inversion algorithms for discrimination.

Response of Magnetic Soils in Magnetic Measurements

Simulation of Soil Magnetic Susceptibility

To evaluate the effect of magnetic soil on the total magnetic intensity (TMI) measurements in UXO detection and discrimination, we assume a general model of susceptibility distribution without too much site-specific information. We represent the 3D susceptibility variation by a 3D grid of cells typically of cubic shape. Given the non-deterministic nature of the soil physical property, we choose to use a correlated random process to represent the spatial distribution of susceptibility. Such a process can be modeled by a power spectrum that decays with the spatial wavenumber and has a random phase term (e.g., Easley et al. 1990 and Shive et al. 1990).

Let \( \chi(x, y, z) \) be the magnetic susceptibility in the 3D volume of subsurface to be modeled, and \( P(\omega_x, \omega_y, \omega_z) \) be its power spectrum, where \( (\omega_x, \omega_y, \omega_z) \) are respectively wavenumbers in the x-, y-, and z-directions. Then the 3D Fourier transform of the susceptibility is given by

\[
\widehat{\chi}(\omega_x, \omega_y, \omega_z) = \sqrt{P(\omega_x, \omega_y, \omega_z)} e^{-i\phi(\omega_x, \omega_y, \omega_z)},
\]  

(1)

where \( \phi(\omega_x, \omega_y, \omega_z) \) is the phase term. Given a power spectrum, we can simulate different realizations of the random process by assigning different random phases. All realizations would have the same power spectrum, and thus have more or less the same appearance in the space domain. However, the locations of features seen in each realization will be different.

In practice, it is often easier to estimate a radially-averaged power spectrum than a 3D spectrum. For this study, we assume a radial power spectrum of the form

\[
P(\omega_r) = \left[ 1 + \left( \frac{\omega_r}{\omega_0} \right)^2 \right]^{-\beta},
\]  

(2)

where \( \omega_r = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2} \) and \( \omega_0 \) is a cutoff frequency and it is inversely proportional to the correlation length of the random process. The parameter \( \beta \) determines how fast the spectrum decays with wavenumber and, thus, how correlated the process is. A value of \( \beta = 0 \) produces a flat power spectrum and corresponds to an uncorrelated random process. Figure 1 displays an example of such a radial power spectrum with \( \beta > 0 \).
To generate the Fourier transform of susceptibility, the last step is to assign values to the phase term. Since the phase is limited to the range of $[0, 2\pi]$, we choose to assign the value as uniformly distributed between $[0, 2\pi]$. Once the Fourier transform of the susceptibility is constructed according to eq.(1), applying inverse transformation yields a susceptibility model in the 3D subsurface volume. The model is then scaled and shifted in DC value to produce a desired susceptibility model with a prescribed mean and standard deviation. Figure 2 displays an example susceptibility model produced by this procedure. Note that the highs and lows of the susceptibility value appear to be randomly located, yet they also occur in blotches with a certain length scale.

**Figure 1.** An example of radial power spectrum described by eq.(1).

**Figure 2.** An example of correlated random susceptibility generated by the procedure described in this section. Note that the highs and lows of the susceptibility value appear to be randomly located, yet they also occur in blotches with a certain length scale.

**Estimating Parameters for Correlated Random Susceptibility**

The preceding section describes a general procedure for generating susceptibility models that can be used in simulating the response of magnetic soils. For meaningful practical applications, we must estimate the defining parameters $\omega_0$ and $\beta$, as well as the amplitude of the susceptibility. These parameters will be site-dependent. For the current study, we have chosen to use information from the Kaho‘olawe, Hawaii, where we estimate the power spectral parameters from TEM data and determine the strength of the susceptibility based on the measured values from soil and rock samples.
Figure 3. Spatial distribution of magnetic susceptibility at Kaho‘olawe, Hawaii. The color image is the strength of 1/t decay of measured TEM data and it is directly proportional to the magnetic susceptibility.

Figure 4. Estimated radial power spectrum. The pluses (+) are the radially-averaged power spectrum of the data shown in Figure 3, and the solid line is the result of least-squares fitting to the functional form in eq.(2).

A set of EM63 data was acquired at the site. Most data located away from buried metal targets exhibit a 1/t decay because of the magnetic viscosity of the top soil at the site. The details of the analysis of these TEM data are presented in (Pasion et al., 2002). The pertinent result for this study is that the strength of the 1/t decaying voltage is proportional to the strength of the magnetic susceptibility at the location of TEM measurement. Plotting the scaling factor $A$ derived from fitting the function $A/t$ to each TEM curve yields the spatial variability of the susceptibility in the horizontal directions. Figure 3 displays a subset of quantity $A$ derived at Kaho‘olawe site. In order to prepare the TEM data for analysis, all the anomalies due to UXO and non-hazardous metal objects were removed, leaving only variations in the data that are due to geology. The data were gridded using a minimum curvature technique. The holes were filled in by interpolation. A second order trend is removed to accentuate the short-wavelength variations that are of interest to this study. We note that this map has a random appearance similar to that in Figure 2, but there are also long-wavelength variations.
Taking the 2D Fourier transform of the data and calculating the radially-averaged power spectrum yields an estimated radial power spectrum of the data set. We then perform a least-squares fit to the functional form in eq.(1) to determine the parameters $\omega_0$ and $\beta$. The result is shown in Figure 4 and the values of the two parameters are $\omega_0 = 2.5$ and $\beta = 1.8$. These values are then assumed to be representative of the spectral property of the soil magnetic susceptibility in 3D at Kaho’olawe site, and we will use them in the subsequent simulations.

**Figure 5.** Theoretical model for examining the effect of soil magnetic susceptibility on total magnetic intensity (TMI) data.

**Figure 6.** Example response (nT) of the soil layer with variable susceptibility and a buried dipole. The dipole is buried at a depth of 0.6 m and the layer has a mean susceptibility value of 0.07 SI.
Figure 7.: Comparison of the radial power spectra of the magnetic field due to a buried dipole (dots) at different depth and due to a 1-m susceptible layer (pluses). All spectra are normalized for comparison. The dipole depth is indicated in each panel. Soil response has the same frequency content as that of a dipole at 1-m depth. Assuming the same magnitude of responses, UXO responses will only be visible when it is buried above that depth.

Figure 6 shows an example of the soil response. The susceptibility in the layer has a mean value of 0.7 SI and the dipole is at a depth of 0.6 m. Panel (a) displays the magnetic anomaly produced by the simulated soil. Panel (b) is the dipole anomaly. The anomalies in the soil response have a length scale comparable to that of the dipole anomaly. Sum of the two is given in panel (c). The dipole anomaly is clearly visible in this case but there are also other highs and lows caused by the soil. We can expect that the presence of these highs and lows will lead to large errors in the recovery of dipole parameters through the inversion, which in turn causes difficulties in discrimination.

Before proceeding to a systematic evaluation on the effect of soil susceptibility, we first develop a qualitative criterion to determine under what conditions the dipole anomaly might be visible in the background soil responses. This can be achieved by examining the power spectra of the two anomalies. Given the assumed parameters of the variable-susceptibility layer and that of the dipole, we can derive the radial power spectrum of the magnetic field produced by either source (Blakely, 1995). For simplicity, we can consider the spectrum of the magnetic anomaly produced by a single layer of cubic cells at the surface of the earth since this layer has the broadest power spectrum. According to Blakely (1995), the power spectrum is given by

\[
P_{\text{layer}} \propto \left[1 + \left(\frac{\omega_\rho}{\omega_0}\right)^2\right]^\beta e^{-2\omega_0 h} (1 - e^{-\omega_0 \Delta z}),
\]

where \(\omega_\rho\) is the radial wavenumber in 2D, \(h\) is the sensor height and \(\Delta z\) is the cell thickness. The power spectrum of the magnetic field produced by a dipole is given by

\[
P_{\text{dipole}} \propto \omega_\rho^2 e^{-2(h+d)\omega_\rho},
\]

where \(d\) is the depth of burial of the dipole. Assuming the spectral parameter \(\omega_0\) and \(\beta\) from the above estimation and the sensor height of \(h = 0.5\) m, we can compare the two radial power spectra for different dipole depths. Figure 7 displays the normalized power spectra assuming three different dipole depths.

At a half-meter depth, the power spectrum of the UXO response is above that of the soil response. Therefore, we have enough high-frequency content in UXO response for it to be detected. When the depth increases to one meter, the two power spectra have the similar relative shape, that means given high enough soil magnetic susceptibility, we can no longer distinguish between the
anomalies produced by the two different sources. Further increasing the dipole depth means that soil response will completely mask the UXO response since the power spectrum of soil response has much more higher frequency contents. It follows that, given the spectral property at Kaho‘olawe, if the UXO anomaly and soil response have comparable magnitude, UXO’s can only be detected directly using magnetic data if they are buried at a depth shallower than 1.0 m.

**Effect of Soil Response on Magnetic Data and its Removal**

*Effects of Soil Response on Inverted Dipole Parameters*

One of the effective UXO discrimination algorithms currently available is based on the magnetic dipole moment recovered from the inversion of surface total-field magnetic anomaly (Billings et al., 2002). In this algorithm, the surface magnetic data measured in the field are inverted to recover six dipole parameters \( m_{mag} = (x, y, z, m_x, m_y, m_z) \) that define the dipole moment, direction, and position. The direction or its deviation from the current earth field is then used to discriminate between UXO and scrap metals. The magnitude of the dipole moment is then used to derive a minimum remanent magnetization for the purpose of classification. Reliable recovery of these parameters is crucial to the success of the algorithm. The anomalies produced by susceptible soil can adversely affect the inversion and hinder the discrimination capability. It is therefore important to quantify the errors caused by the presence of magnetic soil.

To examine the effect, we invert the dipole magnetic data contaminated by soil response and calculate the errors by comparing the recovered dipole parameters with their true values. We carry out this process for different combinations of magnetic susceptibility strengths and dipole depths. The dipole moment is assumed to be 0.5 \( \text{Am}^2 \). This value is based on the dipole moments recovered from the application of the discrimination algorithm to active clearance sites (Billings et al., 2002). The mean susceptibility value ranges from 0.01 to 0.1 in 0.01 increments, and the dipole depth ranges from 0.1 m to 1.2 m in 0.1-m increment. The result is a measure of the error as a function of dipole depth and soil susceptibility. To ensure the reliability of the error estimate, we generate 100 different realizations of the correlated random susceptibility. Thus for each combination of the susceptibility strength and dipole depth, we invert 100 data sets to obtain 100 different recoveries of the dipole parameters. A mean and standard deviation are calculated for the error. The results are detailed in the following.

Figure 8 shows the errors for the recovered dipole position. The panel on the left shows the RMS error in the recovered dipole position and the one on the right shows the standard deviation. The horizontal axis is the true dipole depth and the vertical axis indicates the amplitude of soil susceptibility denoted by its mean value. As discussed above, each point in the map is calculated from 100 different sets of inverted dipole parameters. The error increases with both the dipole depth and amplitude of soil susceptibility. Figure 9 shows the errors for the recovered dipole moment. Figure 10 displays the errors in the recovered dipole direction. There is a similar pattern of large errors with increased soil susceptibility and dipole depth in all three figures. This is expected since an increase in either soil susceptibility or dipole will decrease the relative strength of the dipole response compared to the soil response and therefore lead to large errors in the inversion.

These error maps provide a quantitative indicator by which one can assess the viability of using magnetic data in discrimination. For example, assuming the soil at a site has a similar spectral property as that in Kaho‘olawe, we would not expect magnetic method to be effective if the soil susceptibility is above 0.07 SI. Above this level, both dipole moment and direction recovered from inversion will have too large an error to be useful. Similarly, if the UXO is buried deeper than 1.0 m, even a moderately magnetic soil will mask the dipole response and render the inversion unusable. The results presented
here assume a dipole moment of 0.5 Am$^2$. If the dipole moment is smaller, the above-mentioned threshold of soil susceptibility and dipole depth will decrease since the amplitude of the dipole response will decrease proportionally. A new set of simulation should be performed accordingly.

In general if the combination of the soil susceptibility strength and UXO depth falls within the upper right triangular region of the plots in Figures 8-10, direct inversion of magnetic data for UXO discrimination will be ineffective. In such cases, preprocessing of the data to remove the effect of soil response is required. We present one approach in the following.

![Figure 8](image1.png)

**Figure 8.** Root mean squared (RMS) error and standard deviation of the position of the recovered dipole position. The error is measured as the distance from the true position of the dipole.

![Figure 9](image2.png)

**Figure 9.** RMS error and standard deviation of the recovered dipole moment. The error is measured as the difference between the recovered and true dipole moment.
Removal of Soil Response From Magnetic Data

Like most geophysical inversion, the algorithm for recovering magnetic dipole parameters assumes that the noise in the data is uncorrelated. When this assumption is met, the inversion can separate the signal from noise to a large extent. Difficulty arises when the noise is correlated. Then the noise has the appearance of signal and cannot be easily separated by the inversion algorithm. Such is the case when we have correlated random susceptibility in the soil surrounding a UXO. The anomalies produced by the soil have features similar to that of UXO anomalies. Preprocessing is then required to remove as much noise as possible prior to inversion. Here we propose to use Wiener filter to accomplish this.

Wiener (1949) filter was developed in communication theory to extract a signal from data that are contaminated by noise. This is a Fourier-domain filter defined by the power spectra of different components in the data. Wiener filter assumes there are two components, namely signal and noise, in the data and constructs a transfer function in the Fourier domain such that the filtered data is closest to the desired signal in the least squares sense. Let \( Y(\omega_x, \omega_y) \) be the transfer function, \( \tilde{B}_{\text{obs}}(\omega_x, \omega_y) \) be the Fourier transform of the magnetic data consisting of the dipole and soil responses, the desired dipole response \( \tilde{B}_{\text{dipole}}(\omega_x, \omega_y) \) extracted from the data is given by,

\[
\tilde{B}_{\text{dipole}} = Y \ast \tilde{B}_{\text{obs}}. 
\]  

The transform function is defined by the ratio of two power spectra:

\[
Y(\omega_x, \omega_y) = \frac{P_{\text{dipole}}}{P_{\text{obs}}}, \tag{6}
\]

where \( P_{\text{dipole}} \) is the power spectrum of the dipole response and \( P_{\text{obs}} \) is the power spectrum of the data. The assumption leading eq.(6) is that the signal (dipole response) and noise (soil response) are not
correlated. For practical applications, this filter works well even the assumption is only weakly valid. The key is to have reliable estimate of the power spectra.

In practice, we do not know the power spectrum of the dipole response, which is the quantity we are seeking to extract. However, we can calculate the power spectrum of the observed data and estimate a power spectrum of the soil response by using data that are clearly not affected by UXO responses. Based on the assumption that the soil and dipole responses are not correlated, we can approximate the dipole power spectrum by the difference between the data and soil power spectra. This yields an approximate transfer function that is commonly used to replace the idealized transfer function in eq.(4):

$$Y(\omega_x, \omega_y) \approx \frac{P_{\text{obs}} - P_{\text{soil}}}{P_{\text{obs}}}.$$  \hfill (7)

As an illustration, we apply this filter to a set of severely contaminated data that were generated using the simulated soil and dipole model. The result is shown in Figure 11. The two top panels show respectively the soil and dipole responses. The soil layer has the same spectral property as before, and the mean susceptibility value is 0.07. The dipole is buried at a depth 1.0 m. Figure 11(c) displays the superposition of the two, which simulates the data contaminated by soil responses. There is little visual indication of the presence of a dipole anomaly. This is expected because this combination of soil susceptibility and dipole depth is well within the zone of large inversion errors in Figure 8-10. Figure 11(d) is the result obtained by applying Wiener filter. The data power spectrum is estimated from the Fourier transform of the data, and the power spectrum of the soil response is estimated from the data in Figure 11(a). We can see that now a dipole anomaly is clearly visible. Inversion of the processed data is also expected to produce much better results.

This is demonstrated by the results shown in Table 2, which compares the dipole moment ($m$) and dipole direction (declination $D$ and inclination $I$) recovered from inverting the raw data in Figure 11(c) and the processed data in Figure 11(d). The second column lists the true values of these parameters. The third lists the values recovered from the raw data. There are large errors. The fourth column lists the improved results obtained from inverting the preprocessed data and they are much improved.

**Conclusions**

We have examined the effect of magnetic soil on static magnetic method used in the UXO discrimination problems. We have developed quantitative understanding of the effect and proposed a simple processing technique to alleviate the soil effect and increase the reliability of the model parameters inverted from magnetic data sets used in discrimination.

Spatial variation of the static magnetic susceptibility is modeled using a correlated random process in 3D. The spectral properties of the random process are estimated from the field data observed at Kaho‘olawe clearance site and then used in the simulations. Numerical modeling and inversion provide clear indication of the condition under which the magnetic soil can completely mask UXO response. We have found that Wiener filter is effective in suppressing the soil response as a preprocessing tool. However, its effectiveness depends critically upon our ability to estimate the power spectrum of the soil response. In general, the filtered result will be useful for detection purposes, but it may not be sufficient for discrimination purposes. Reliable estimation of the power spectrum of soil response depends on good characterization of spatial variation of susceptibility at the clearance site. Further work using field data at sites with strong magnetic soil is therefore required.
Figure 11. Example of Wiener filtering applied to remove the effect of soil responses. Top panels show respectively the magnetic data (nT) generated by the soil with a mean value of 0.07 SI and a dipole at a depth 1.0 m. Lower left panel is the superposition of the two, and lower right panel is the extracted dipole response by using the Wiener filtering.

Table 2.: Comparison of the true dipole parameter with those recovered from soil contaminated data and from Wiener filtered data. In the table, $m$ denotes the dipole moment, $D$ is the declination of the dipole direction and $I$ is the inclination.

<table>
<thead>
<tr>
<th></th>
<th>Real Value</th>
<th>With Soil Response</th>
<th>Wiener Filtered Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m$</td>
<td>0.5</td>
<td>1.8</td>
<td>0.2</td>
</tr>
<tr>
<td>$D$</td>
<td>9.8</td>
<td>10.0</td>
<td>11.7</td>
</tr>
<tr>
<td>$I$</td>
<td>36.2</td>
<td>-11.6</td>
<td>27.9</td>
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