Use of principal component analysis in the de-noising and signal-separation of transient electromagnetic data

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Abstract

We present a method based on principal component analysis (PCA) for suppressing noise and separating signal sources in transient electromagnetic (TEM) data acquired in environmental clean-up and hydrogeophysical applications. Coherent noise due to background responses and incoherent noise often contaminate data in these applications and preprocessing is required for quantitative analyses. In these problems, either central-loop configuration over closely spaced stations or fixed-loop setup with multiple stations is used. Resulting data are ideal for decomposition by PCA. In this paper, we outline the basics of PCA and apply it to the processing of TEM data from unexploded ordnance (UXO) clearance. We demonstrate that PCA can clearly separate the background geologic noise due to magnetic soil and suppress incoherent noise contaminating data in late time gates.
Keywords: transient electromagnetic, noise, principal component analysis, signal separation

Introduction

Transient electromagnetic (or time-domain) methods have applications over a wide range of scales. Small-scale, near-surface surveys for unexploded ordnance investigate the subsurface within a meter or so, intermediate-scale groundwater mapping operates with a target depth of hundreds of meters, whereas applications in resource exploration extend to kilometer depths. The inductive TEM method uses a loop source to generate a time-varying magnetic field. This field at the surface induces electrical currents in the host medium (ground), and more importantly in conductive targets. Once induced, these currents dissipate over time due to ohmic losses, leading to a measured transient decay in magnetic field flux density at the surface by geophysical sensors. The currents induced in the surrounding medium and in the conductive targets decay at different rates and thus can be separated. For compact objects, the decay rates are directly related to the size, shape, and electrical conductivity of the target body. Inductive transient electromagnetic surveys are advantageous in their versatile capability which is required for such a wide range of targets. Unfortunately, the TEM method is not impervious to noise, geologic and otherwise, at different scales.

Current methods of noise analysis in TEM surveys often do not adequately and consistently remove both correlated noise (geologic, instrument, coil orientation, microtopography, and others) and uncorrelated noise (RF interference, telluric sources, instrument electronics). Each of these sources of noise (in addition to the signal from the target) contributes to the total response measured by the sensors. The effect of noise is especially strong at late-times in TEM data. Noise from such numerous and varying sources often limits the ability of the TEM method and the effect is especially severe when the desired signal is weak or the host response is strong. For example, the time-lapse signal in hydrogeophysical problems is embedded in large host responses, which limits the ability to determine aquifer parameters or map groundwater movement with time. Similarly, the response from magnetic soil, ambient noise, and instrument movement often hampers adequate detection and discrimination of hazardous munitions from non-hazardous items in UXO clearance. Thus, there is a need for methods to enhance TEM data at all scales.

We present a principal component analysis (PCA) based method for both the attenuation of random, uncorrelated noise, as well as the identification of signal due to the target and due to other geologic effects. We develop the PCA method for TEM surveys using a Karhunen-Loéve Transform as the linear transform operation. We will then illustrate the application of PCA-based de-noising and signal separation using synthetic and field examples from unexploded ordnance clearance.

Principal Component Analysis

Principal component analysis is a statistical method for analyzing observations in multiple channels through an orthonormal projection. Not only does principal component analysis have the ability to remove uncorrelated noise, but also to decompose a signal into constituent components from its sources in many cases. Consequently, PCA has been used for many different applications including digital image enhancement, data transmission and compression (Jones and Levy, 1987), de-noising radiometric data (Minty and Hovgaard, 2002), and seismic de-noising (Jones and Levy, 1987; Jackson et. al., 1991). Recently, it has been applied to airborne EM (AEM) surveys to construct intuitive RGB maps based on the principal components (Green, 1998).

Although PCA methods vary greatly in their application, they are all similar in that they deconstruct a multi-channel signal into a set of orthogonal bases of decreasing energy. These sets can be reconstructed into the original signal exactly, or a truncated set can be used in reconstruction that tends to eliminate noise. Correlated signals are typically reconstructed by adding the bases (from highest to lowest energy) until the desired energy level is reached—generally chosen through a statistical analysis of error.

In most surveys with multiple stations that record traces (decay curves) of data, there are two dimensions over which a signal can be said to be “correlated.” One can analyze the correlation between time-slices or between traces. In essence, we are either analyzing similarities in anomaly geometry or similarities in decay. Which correlation we analyze will have important implications on computation cost of the calculations.

Mathematical Development of PCA

Geometrically, the data set from a TEM survey can be envisioned as a cloud of ‘*m* x *n*’ measurements in an *n*-dimensional data space (where *m* is the number of channels and *n* the number of stations, for purposes of the derivation). The data coordinate system is rotated until the first axis is along the direction where the data has the greatest variance. The second coordinate axis is chosen to have the next highest data variance subject to the constraint that it must be orthogonal to the first, and so on (Green, 1998).

To define these principal components, we introduce the Karhunen-Loéve Transform as a linear PCA tool as in Jones and Levy (1987). However, any eigenvector or singular value decomposition will produce an equivalent result to the accuracy of that decomposition (Minty and McFadden, 1998).

Given a set of data consisting of multiple traces each with multiple data values

$$x_i(t_j), \quad i = 1, \cdots, n;\ j = 1, \cdots, m$$

where the *i*’th trace is associated with a particular location and the index *j* corresponds to a particular channel of observation at that given location. For example, one may have an EM63 instrument occupying *n* locations along a line or within a grid during a UXO survey, which would yield *n* traces of decaying voltage, each containing 25 channels of data ($m = 25$). As stated earlier, principal component analysis (PCA) first generates a rotation matrix that rotates the data traces onto a set of orthogonal directions called principal component directions. In such a rotation, the resulting components are ordered by decreasing energy. The earlier components with most energy tend to capture the coherent data signal whereas the later components tend to represent incoherent noise in the entire data set.

Such a rotation matrix can be defined by decomposing the covariance matrix Γ of the data traces. The elements of covariance matrix are given by:

$$\gamma_{kl} = \sum_{j=1}^{m} x_k(t_j) x_l(t_j),, \quad k, l = 1,\ldots, n. \tag{1}$$

The covariance matrix Γ can be decomposed into its corresponding eigenvalues and eigenvectors:

$$\Gamma = R \Lambda R^T, \tag{2}$$

where Λ is a diagonal matrix consisting of the eigenvalues of Γ and R is the eigenvector matrix whose columns are the corresponding eigenvectors. Kramer and Mathews (1956) showed that the eigenvectors define the principal component directions and matrix R^T is exactly the rotation matrix that decomposes (or rotates) the original signal into such components:

$$\psi_k(t) = \sum_{i=1}^{n} r_{ki} x_i(t) \quad k = 1, \ldots, n, \tag{3}$$

and the original signal can be reconstructed by:

$$\tilde{x}_i(t) = \sum_{k=1}^{n} r_{ik} \psi_k(t), \; i = 1, \ldots, n, \tag{4}$$

Using a compact notation with a data matrix X whose rows are the data traces, the decomposition (Ψ) and reconstruction can be written as

$$\Psi = R^T X \text{ and } \tilde{X} = R\Psi . \tag{5}$$

We note that the eigenvector matrix R is a unitary matrix and satisfies:

$$RR^T = R^T R = I ,$$

where I is an identity matrix. Thus the reconstruction is exact and unique, and the data matrix X is equal to:

$$X = \tilde{X} = RR^T X . \tag{6}$$

Mathematically, the reconstructed signal is exactly equal to the original signal when all principal components are included. Reconstructing with a selected subset of principal components $\psi_k(t)$ would yield a truncated reconstruction that is devoid of the energy captured in the discarded components. For example, incoherent noise often populates the last few principal components and discarding them during reconstruction would yield a cleaner signal that is minimally affected by the noise. Thus to perform simple de-noising of signals, the reconstruction series is truncated as:

$$\tilde{x}_i(t) = \sum_{k=1}^{c} r_{ik} \psi_k(t) \quad c < \text{n}, \tag{7}$$

although other reconstruction schemes are also possible. In matrix notation:

$$\tilde{X} = RBR^T X , \tag{8}$$

where B is a diagonal matrix, with ones at the rows corresponding to the components used for reconstruction, and zeros everywhere else. This result is derived from the fact that PCA measures *correlated* energy. If a signal is random from trace to trace then there is very little correlated energy between the signals, so the reconstruction of those signals falls to the later components. For this reason, truncation of the rotated matrix is an extremely fast process to remove uncorrelated noise from data.

The strength in PCA, however, comes not only from the removal of uncorrelated noise, but also from correlated signals that contaminate the desired signal. If signals recorded from different sources contain different characteristics (i.e. unexploded ordnance and geology), PCA is able to separate them into specific components. More importantly, only the signals due to the desired source can be reconstructed by choosing the appropriate principal components.

Synthetic Example

In order to demonstrate the ability of PCA to remove correlated noise as well as uncorrelated noise, we present a synthetic TEM dataset. The data contain geometry from a real UXO survey, with actual yaw, pitch, and roll values from the recorded movement of an EM63. This movement results in an imprinted noise over the half-space response. Contained in this half-space are evenly placed 60mm mortar rounds. The TEM response of these factors was calculated, and pseudo-random noise was added. The data set contains approximately 134000 observation stations and 25 time gates for each decay curve. Figure 1 shows the first time gate in map format.

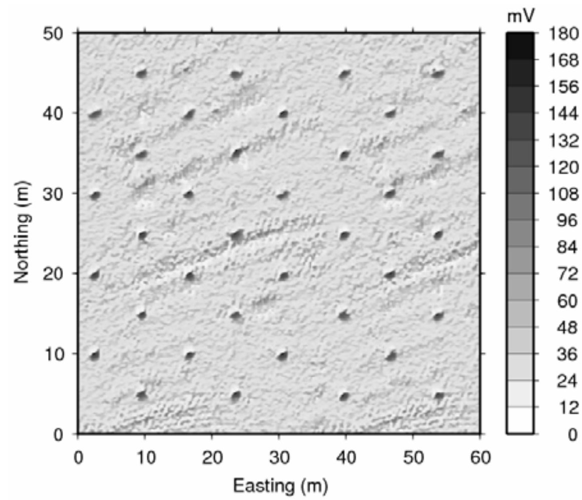

Figure 1. First time gate of EM-63 data simulated with 60mm mortar rounds in a half-space and errors produced by instrument orientation variations.

Although the response due to UXO is clearly visible in the original data, detection algorithms can be "confused" by the presence of signal due to orientation error. Figure 2 shows the dataset after a "blind" principal component analysis constructed with the second through twenty-fifth principal component. The signal due to orientation error has been removed. Although the amplitude of the anomalies due to ordnance has been reduced, detection algorithms no longer must contend with the undesired signal, leading to more complete detection. With the location of the ordnance known, discrimination algorithms can be applied to only windowed areas, reducing the number of false positives and reducing computation time.

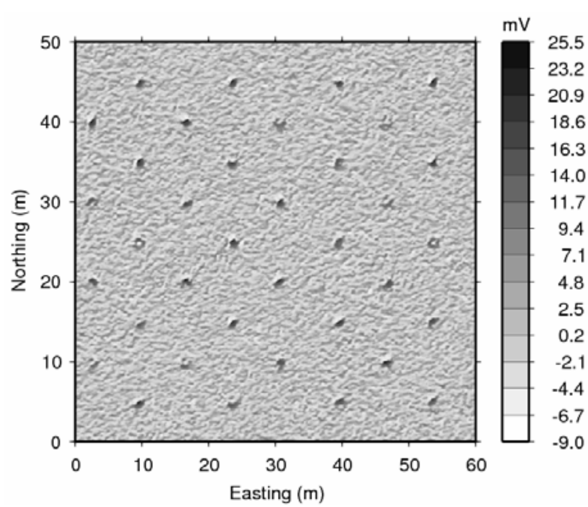

Figure 2. Simulated data after construction without the first principal component. Although the magnitude of the anomalies has been reduced, the dataset is fully prepared for an automatic detection algorithm.

Field Example

To show the de-noising capability of PCA, we study an example dataset from Kaho'olawe, Hawaii, USA. The TEM data (collected with a Geonics EM-63) come from a 30 meter by 60 meter grid set on extremely magnetic soils (magnetite, titanomagnetite, and ilmenite) due to volcanism. Weathering of the volcanics in the tropical climate led to soils exhibiting high degree of frequency dependence in magnetic susceptibility. The spatially variable, frequency-dependent susceptibility produces strong *1/t* decay that masks the UXO response in EM63 data. The soil response is over 400 mV in gate-1 across the survey area spanning 30 m on a side (Figure 3). In addition, the instrument movement, ambient interferences, and other sources lead to the ubiquitous noise in late time gates.

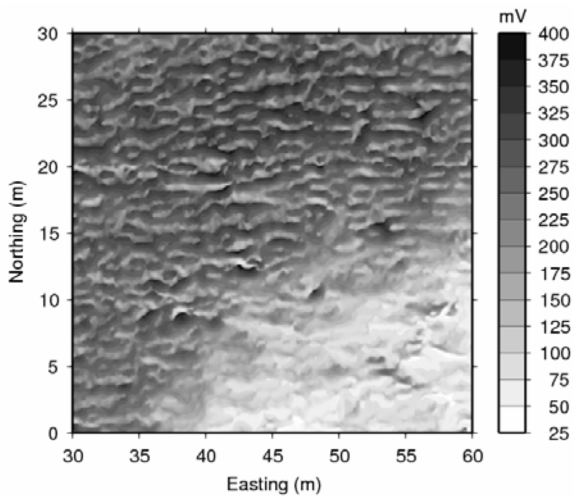

Figure 3. First time gate of EM-63 data collected over the Kaho'olawe Navy QA grid. Note the large geologic response due to Viscous Remnant Magnetization (VRM).

To assist with the separation of the magnetic soil response from unexploded ordnance, we must first attenuate the noise in the late time gates. The strong soil response masks much of the signal due to UXO before the last few time gates, so improvement in signal-to-noise is paramount in interpretation.

The data (consisting of approximately 23000 decay curves of 25 gates each) were decomposed into constituent principal components and re-composed using a subset of those components. Figure 4a shows a set of the original data that include only geologic response as well as data that have signal from UXO imprinted on the decay curves.

Magnetic soil at Kaho'olawe (and in general) exhibits a t^{-1} decay in TEM surveys (Pasion et. al., 2002). This signal is clearly present in the raw data. Reconstruction with only the first principal component reveals this decay due to the magnetic soil (Figure 4b). Traces with UXO and those without UXO are indistinguishable. However, when the second principal component is added (Figure 4c), the signal from the UXO (deviation from t^{-1} decay in later time gates) is clear. The random, uncorrelated noise that contaminated these later time gates is severely reduced without attacking the amplitudes of the decay curves, preparing them for numerical discrimination analysis with other methods.

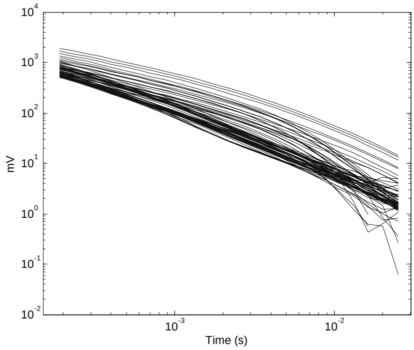

Figure 4a. 65 example decay curves from Kaho'olawe. Some traces include responses from unexploded ordinance; these traces deviate from the expected t^{-1} decay.

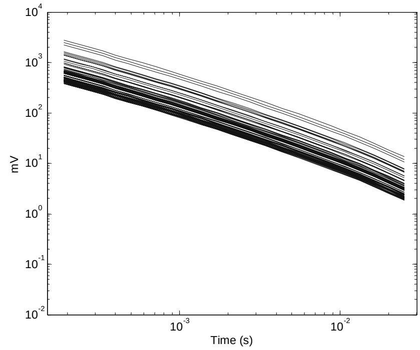

Figure 4b. Geologic response constructed with only the first principal component. The curve exhibits the expected inverse power law decay due to horizontal layering and magnetic soils.

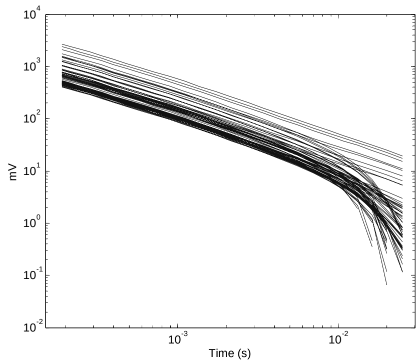

Figure 4c. TEM decay curves constructed with the first and second principal components. The (approximate) superposition of UXO signal on the geologic signal is clear, with significant reduction of random noise in later channels. (Negative values not displayed)

Conclusions

Principal component analysis has the capability to attenuate random, uncorrelated noise in multi-channel data, as well as separate out signals from sources with different characteristics. Even in severely magnetic environments PCA can reduce noise, especially in late time gates (where the unexploded ordnance signal is dominant). In synthetic data, we show that the characteristics of the heading/orientation errors in TEM data are sufficiently different from the characteristics of UXO response such that PCA can cleanly separate the signals. Application of the PCA algorithm prepares TEM data for subsequent numeric processing. Whether the objective is to detect unexploded ordnance automatically or clean late gates of TEM data in a groundwater survey, proper choice of principal components can yield a dataset that highlights the desired signal and suppresses noise.

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