Robust processing of onshore controlled-source electromagnetic data from a three-phase galvanic source

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SUMMARY

High-quality data is key to any meaningful inversion. Whereas robust processing techniques are routinely used for estimating high-quality magnetotelluric (MT) transfer functions, such techniques are not commonly applied for controlled-source electromagnetic (CSEM) processing, although CSEM and MT data exhibit similar noise characteristics. We have implemented a new CSEM processing scheme that combines CSEM-specific preprocessing and statistically robust least-squares stacking to extract interpretable ground responses from noisy CSEM data. We apply this processing scheme to signals from a new CSEM transmitter that is equipped with three grounded electrodes and allows us to generate signals at multiple source polarizations with relatively little field effort. For this transmitter setup, we can formulate a bi-variate relation between the source currents injected through any two of the source electrodes and the recorded EM field components. This leads to an over-determined system of equations that includes all available data from multiple source polarizations and is solved for the ground responses in a robustly weighted least-squares sense. This process also provides error estimates that are directly fed into subsequent 1D and 3D inversion. We demonstrate the retrieval of CSEM responses from data recorded in an area heavily affected by various sources of strong cultural noise, including cathodic protection systems, wind power plants and major power lines.

Keywords: land CSEM, processing, robust statistics

INTRODUCTION

Magnetotelluric transfer functions are commonly estimated by robustly weighted least-squares procedures (e.g., Egbert & Booker, 1986) to reduce the impact of cultural noise on the transfer function estimates. Controlled-source electromagnetic data are plagued by the same cultural noise as MT data. For CSEM measurements on land, a large portion of the signal propagates through the air, such that the imprint of subsurface features on land CSEM data is small compared to marine data. At the same time, without the presence of an attenuating water layer and for measurements commonly carried out in populated areas, noise levels in land CSEM data must be expected to be much higher than in marine data.

Many previous land electromagnetic studies process and interpret the data in the time domain, with the primary intent to reduce the 'airwave' influence (e.g., Ziolkowski, Hobbs, & Wright, 2007). However, time-domain signal recorded during transmitter switch-off typically has low amplitudes and may therefore be even more sensitive to noise than frequency-domain data. Specific noise filters adjusted to the characteristics of transients have been developed (Strack, Hanstein, & Eilenz, 1989), yet the interpretation of low-amplitude tails of transients for deep structure remains difficult. We investigate the interpretation of land CSEM data in the frequency domain. Unlike marine data that are commonly recorded with moving sources and thus provide only limited possibilities for quality enhancement by processing, land CSEM data typically contain records over long times from stationary sources. Nonetheless, robust processing techniques analogous to those used for MT transfer function calculation have not commonly been applied to CSEM data.

Whereas cultural noise in MT and CSEM data is identical, the characteristics of MT and CSEM signals differ significantly. Ideal MT signal is assumed to be generated by plane-wave sources at a uniform distribution of polarizations, with a continuous spectrum, yet not necessarily periodic. In contrast, CSEM signal originates from a distinct source location and contains energy at the discrete frequencies excited by the source. It usually has a well-defined polarization and is quasi-periodic when transmitting multiple cycles of the same source waveform. Therefore, it is not clear *a priori* that robust MT processing approaches are beneficial for CSEM processing. Clearly, the preprocessing that provides the Fourier coefficients used in robust stacking has to take into account the specific CSEM data properties. Also, records of CSEM source signals can be assumed to be effectively noise-free. Therefore, remote reference techniques analogous to those used in MT to reduce bias due to noise in the magnetic field channels are not necessary in CSEM.

We have implemented a robust CSEM processing scheme. In this contribution, we first describe our processing flow, which should be generally applicable to land CSEM data, and which we use for estimating bivariate response functions from a three-phase transmitter. We then show processing results for very noisy land CSEM data recorded across the CO_2 storage test site at Ketzin, Germany.

BIVARIATE ROBUST CSEM PROCESSING

We consider a transmitter having three grounded electrodes, through which we inject into the subsurface three versions of a given current waveform that are phase-shifted to one another by 120° (Figure 1). The currents can be written as

$$I_k = I(\omega)\cos\left((k-1) * 120^\circ + \phi\right);\ k \in (1,2,3)\,, \quad (1)$$

where I is the source waveform, ω is the angular frequency, and the angle ϕ can be adjusted to vary the distribution of currents on the three electrodes and thus change the source polarization.

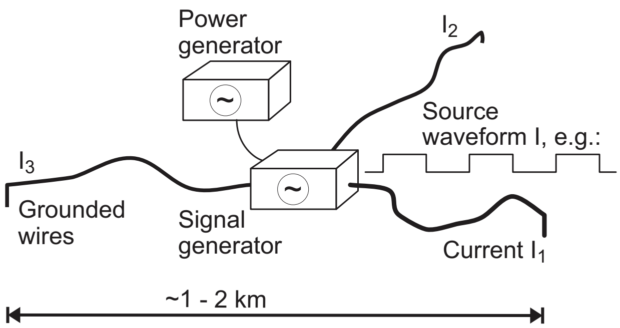

Figure 1. Principle sketch of the three-electrode, three-phase transmitter considered.

The recorded data (e.g., E_x) at position $\mathbf{r}$, transformed to the frequency domain, can be expressed as (de Hoop, 1995)

$$E_x(\mathbf{r}) = j\omega\mu_0 \int_S \mathbf{G}^{EJ}_{E_x}(\mathbf{r} \mid \mathbf{r}')\,\mathbf{J}(\mathbf{r}')\,\mathrm{d}\mathbf{r}'. \quad (2)$$

Here, $j = \sqrt{-1}$, μ_0 is the free-space magnetic permeability, the integration is carried out over the source volume S, $\mathbf{G}^{EJ}_{E_x}$ is the Green's function vector for E_x due to electric dipole sources, and $\mathbf{J}$ is the source current density. For our transmitter consisting of three wires of small diameter and currents assumed to be constant along each wire, this simplifies to

$$\mathbf{E}(\mathbf{r}) = j\omega\mu_0 \sum_{k=1}^{3} I_k \int_{L_k} \mathbf{G}^{EJ}_{E_x}(\mathbf{r} \mid \mathbf{r}') \cdot \mathrm{d}\mathbf{l}', \quad (3)$$

where we integrate over the length L_k of each wire. The integrals in Equation 3 describe the ground responses for a given source geometry, but are independent of the current amplitudes. Introducing shorthands $T^{E_x}_k$ for these response function integrals, we rewrite Equation 3 as

$$E_x(\mathbf{r}) = \sum_{k=1}^{3} I_k T^{E_x}_k, \quad (4)$$

where the constant $j\omega\mu_0$ has been included into $T^{E_x}_k$. Because the three currents are linearly dependent with $\sum_{k=1}^{3} I_k = 0$, it is impossible to determine the three separate transfer functions $T^{E_x}_k$. Instead, we eliminate one of the currents from Equation 4. For example, eliminating I_3 results in

$$\begin{aligned} E_x(\mathbf{r}) &= I_1\left(T^{E_x}_1 - T^{E_x}_3\right) + I_2\left(T^{E_x}_2 - T^{E_x}_3\right) \\ &= I_1 T^{E_x}_{1,3} + I_2 T^{E_x}_{2,3}. \end{aligned} \quad (5)$$

This expression for the combined response functions $T^{E_x}_{1,3}$ and $T^{E_x}_{2,3}$ in Equation 5, and analogous response functions for the other field components, is formally identical to the expression describing magnetotelluric transfer functions. Provided that we have recorded multiple samples (i.e., time windows) of E_x with at least two different sets of source currents I_1 and I_2, we can determine the responses $T^{E_x}_{1,3}$ and $T^{E_x}_{2,3}$ by least-squares fitting of Equation 5.

To obtain robust response function estimates, we adopt a procedure known to work for single-station MT transfer function estimation (Weckmann, Magunia, & Ritter, 2005; Krings, 2007). Starting from an ordinary least-squares estimate of the response functions, we compute predicted data E^p_x. We determine an initial guess for the standard deviation σ of the residuals $E^p_x - E_x$ based on their median absolute deviation (Huber, 1981). We then define Huber weights that downweight data for residuals larger than 1.5σ, and recalculate response functions and residuals from the weighted data. The standard deviation σ is re-estimated based on the mean of the weighted residuals. We have tested iteratively repeating this procedure until changes of the response function estimates are minor, yet this did not result in consistent improvement of the response functions. Instead, to prevent strong outliers from distorting the result, we define Tukey weights with a tuning constant of $c = 4.685$ (Holland & Welsch, 1977), reweight the data and recompute the response functions. Data for residuals larger than $c\sigma$ are ignored in this final estimate. Lastly, following Junge (1993) and Egbert and Booker (1986), we calculate a 2×2 covariance matrix that provides an indication of the uncertainty of the response functions. These error estimates are used directly for CSEM inversions (Grayver, Streich, & Ritter, 2013).

Application to field data

To obtain Fourier coefficients from CSEM time series, we first remove the strongest noise peaks at the railway network frequency of 16.7 Hz and the power grid frequency of 50 Hz and its multiples using a time-domain notch filter (Strack, 1992). All filters applied to the receiver data are identically applied to the source data to preserve data consistency. To prevent Fourier transform artifacts, we then apply a drift correction filter (Friedel, 2000) that removes signal at periods longer than the source period. Next, we cut the data into time windows as long as the source period, and apply a taper, typically only a few samples long, to the ends of each window. We Fourier transform the data, extract the spectral components excited by the source, and deconvolve the measured responses of the sensors and recording instruments.

For robust stacking, we combine all available data within log-equispaced frequency bins, typically using ∼5–8 frequency samples per decade. If data for at least three different frequency values exist within a bin, the stacked result is assigned to the bin center. This frequency binning results in large amounts of data falling in high-frequency bins, thus allowing us to utilize low-amplitude data at large multiples of the source frequency.

Figure 2 shows an example of response functions for data collected across the CO_2 storage test site at Ketzin, Germany (Streich, Becken, Matzander, & Ritter, 2011). The responses are estimated from about 12.5 hours of signal transmission at source frequencies between 1/64 and 64 Hz. The source signal includes mainly square waves, and one hour of pseudo-random binary sequences. For each source frequency, we used signal up to 100 times the source frequency. Signal in overlapping frequency bands from transmission at different frequencies were stacked jointly.

The site shown was located only 600 m from a pipeline that carried cathodic protection currents pulsed at a 15-s period. Accordingly, very strong pipeline noise was present in the data. Without robust weighting, data within a wide frequency range are strongly distorted and would be impossible to interpret (Figure 2a, b). With robust weighting, the response functions vary smoothly with frequency, as is expected for diffusive EM fields.

We applied the robust processing to the entire data set containing data from eight transmitters recorded by 39 receivers. Figure 3 shows an example for a transmitter located near the start of the receiver line. Robust stacking has resulted in response functions consistent in frequency and space. The responses remain somewhat noisy only in the center of the profile, where the pipeline crosses the receiver line, and near the far end, where data amplitudes are low and additional noise is generated by an array of wind power plants.

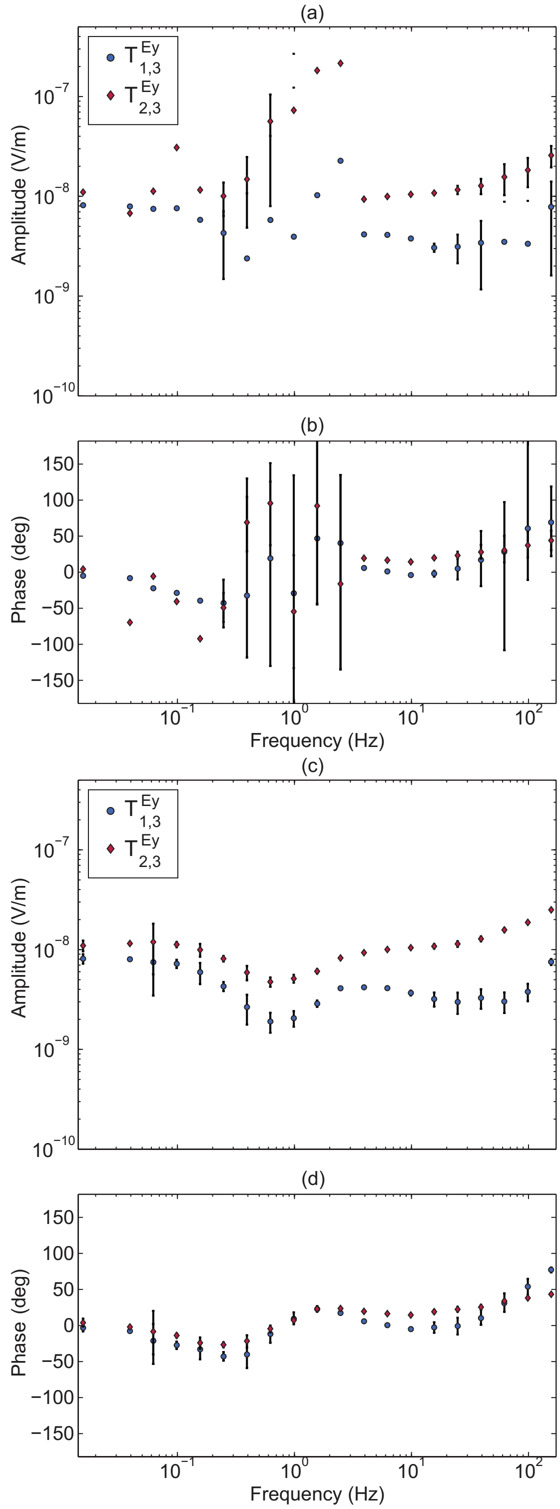

Figure 2. Example of processing results for the electric field Ey, for a transmitter located ∼4.5 km from the receiver, and strong noise generated by pulsed anti-corrosion currents from a nearby gas pipeline present in the data. Results are shown for (a, b) simple least-squares stacking and (c, d) robustly weighted stacking.

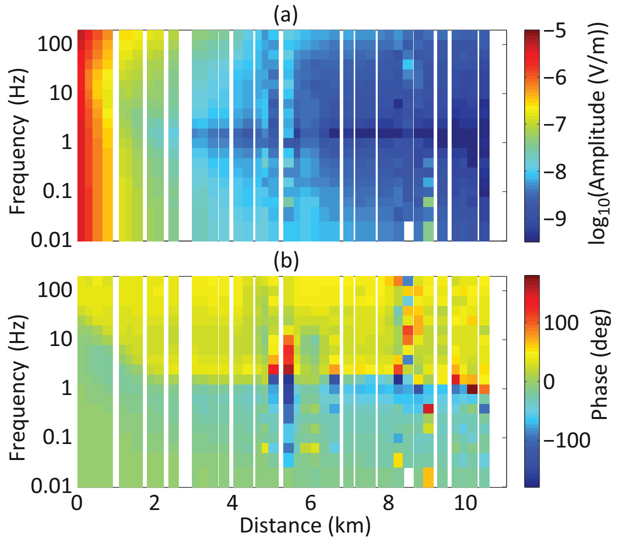

Figure 3. (a) Amplitude and (b) phase of response functions $T_{1,3}^{E_x}$ for a line of receivers, and a transmitter located ∼1 km from the start of the profile. Every vertical line corresponds to one receiver.

DISCUSSION AND CONCLUSIONS

The quality of land-based CSEM data is improved enormously by robust processing analogous to MT transfer function estimation. Robust approaches may not be necessary in remote regions, and would be difficult to apply for marine data collected with moving sources. However, in a high-noise populated area where ordinary least-squares failed to provide useful results, robustly weighted stacking has provided invertible and interpretable data. Further improvement of data quality is desirable and may be attempted by designing site-specific filters.

Beside assessing the error estimates provided by the robust stacking procedure, additional quality control is possible by exploiting the dependency between the response functions $T_{1,2}$, $T_{1,3}$ and $T_{2,3}$ to synthesize one of them from the two others. The robust stacking approach described here for bivariate response function calculation can also be applied for univariate processing of data from a single source polarization or standard dipole sources.

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