Data Processing of Controlled Source Audio Magnetotelluric (CSAMT) Data

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Abstract

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During this project three distinct methods to improve the data processing of Controlled Source Audio Magnetotellurics (CSAMT) data are implemented and their advantages and disadvantages are discussed. The methods in question are:

- Detrending the time series in the time domain, instead of detrending in the frequency domain.
- Implementation of a coherency test to pinpoint data segments of low quality and remove these data from the calculations.
- Implementing a method to detect and remove transients from the time series to reduce background noise in the frequency spectra.

Both the detrending in time domain and the transient removal shows potential in improving data quality even if the improvements are small (both in the (1-10\% range). Due to technical limitations no coherency test was implemented. Overall the processes discussed in the report did improve the data quality and may serve as groundwork for further improvements to come.

**Key words:** CSAMT, detrending, coherency, transients, time series, processing

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Sammanfattning

Data processering av ”Controlled Source Audio Magnetotelluric” (CSAMT) data

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Projektet behandlar tre stycken metoder för att förbättra signalkvaliten hos Controlled Source Audio Magnetotellurics (CSAMT) data, dessa implementeras och deras för- och nackdelar diskuteras. Metoderna som hanteras är:

- Avlägsnandet av trender från tidsserier i tidsdomänen istället för i frekvensdomänen.
- Implementationen av ett koherenstest för att identifiera ”dåliga” datasegment och avlägsna dessa från vidare beräkningar.
- Implementationen av en metod för att både hitta och avlägsna transienter (data spikar) från tidsserien för att minska bakgrundsbruset i frekvensspektrat.

Både avlägsnandet av trender samt transienter visar positiv inverkan på datakvaliteten, även om skillnaderna är relativt små (båda på ungefär 1-10%). På grund av begränsningar från mätdata kunde inget meningsfullt koherenstest utformas. Överlag har processerna som diskuteras i rapporten förbättrat datakvaliten och kan ses som ett grundarbete för fortsatta förbättringar inom området.

Nyckelord: CSAMT, detrending, koherens, transienter, tidserier, processering

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Contents

1 Introduction ............................................. 1
  1.1 Project background ................................ 1
  1.2 Aim of the project ................................. 1

2 Theoretical Background ............................. 1
  2.1 CSAMT ............................................. 1
  2.2 CSAMT measurement work flow .................... 4
  2.3 Drift removal & filtering .......................... 5
  2.4 Signal coherency ................................. 8
  2.5 Transients in time series ......................... 11

3 Method ..................................................... 13
  3.1 Drift removal in time domain ..................... 13
  3.2 Signal coherency test ............................ 14
  3.3 Transient detection and removal ................. 14

4 Results .................................................... 15
  4.1 Drift removal in time domain ..................... 15
  4.2 Signal coherency test ............................ 16
  4.3 Transient removal ................................ 16
  4.4 Effect on transfer functions ..................... 19

5 Discussion ............................................... 22
  5.1 SN-ratio from drift removal ..................... 22
  5.2 Limitations of the standard EM coherency model 22
  5.3 Tapering of transients ........................... 23
  5.4 Changes in transfer functions ................. 23

6 Conclusions .............................................. 23

7 Acknowledgements ..................................... 24

References ............................................... 24

Appendices ............................................... 26

A Code to find R value ................................. 27
B Code to identify transients ......................... 28
C Code to create filters ................................ 29
D Code to filter time-series ............................ 30
E Data used in calculating SN ratios for result ....... 31
1 Introduction

1.1 Project background

Controlled Source Audio Magnetotellurics (CSAMT) and Controlled Source Electromagnetics (CSEM) are relatively new and rapidly growing methods within applied geophysics. Using a transmitter, a known electromagnetic signal is sent through a medium where the response is measured at several receiver sites. This results in a time series measurement of both the electric and magnetic field components \( (E_x, E_y, H_x, H_y, H_z) \).

Using robust data analysis, removing noise and fitting the data the electrical properties of the media can be retrieved with acceptable accuracy in subsequent inversion. This prediction is used to create a model of changes in material within the earths crust, finding fluids like ground water or oil as well as mineral deposits and other natural resources. Magnetotelluric methods have recently (1970-forward) been adopted and used widely in both prospecting and mineral exploration as well as groundwater surveys by both industry and the scientific community. Chave & Jones (2012)

1.2 Aim of the project

One of many aspects of CSAMT investigations is the data analysis, and the main part of this project is to implement several methods to strengthen the data analysis process. To achieve this improvement, focus is put on the reduction of noise in the data and thus improving the accuracy of the final results. The main source of noise can be identified as man-made noise mainly from the electrical grid, railway lines or industrial machinery. Examples are given and discussed by Pankratov & Geraskin (2010) and Streich et al. (2013). In this project three methods are to be tested: trend removal in the time domain, a coherency test for the components used constructing the impedance tensor and removing data transients to improve the overall data quality. This will hopefully improve the data for further analysis. The data used during the project is CSAMT data measured by Uppsala University.

2 Theoretical Background

2.1 CSAMT

In this chapter some of the concepts and equations behind CSAMT are derived, Chave & Jones (2012) and Zonge & j. Hughes (1991) have been used as sources and discusses the whole derivation in more depth. CSAMT being an electromagnetic method is fundamentally based upon Maxwell’s equations:

\[
\begin{align*}
\nabla \times \vec{E} &= \frac{\delta \vec{B}}{\delta t} \\
\nabla \times \vec{H} &= \vec{J} + \frac{\delta \vec{D}}{\delta t} \\
\nabla \cdot \vec{D} &= q_e \\
\nabla \cdot \vec{B} &= 0
\end{align*}
\]

(1)

where \( \vec{E} \) and \( \vec{D} \) are the electric field and electric displacement field respectively and \( \vec{B} \) and \( \vec{H} \) are the magnetic flux and magnetic fields respectively. \( q_e \) is the free charge and \( \vec{J} \) is the free current density. From these one can extract the two wave equations for \( \vec{E} \)
and $\vec{H}$.
For homogeneous media and no external source these are:

$$\begin{align*}
\nabla^2 \vec{E} + \gamma^2 \vec{E} &= 0 \\
\nabla^2 \vec{H} + \gamma^2 \vec{H} &= 0
\end{align*}$$

(2)

where $\gamma$ is the propagation constant that is defined as:

$$\gamma = \sqrt{\omega \mu (i \sigma - \omega \epsilon)} : \text{Re}(\gamma) > 0$$

where $\omega$ is the angular frequency, $\mu$ is the magnetic permeability of the traversed media, $i$ is the imaginary unit making $\gamma$ complex valued, $\sigma$ is the electrical conductivity of the media and $\epsilon$ is the dielectric permittivity of the media.

$\gamma$ being complex valued can be written in the form: $\gamma = \alpha - i\beta$ where $\alpha$ and $\beta$ are the phase and attenuation constants respectively:

$$\begin{align*}
\alpha &= \omega \sqrt{\frac{\mu \epsilon}{2} (\sqrt{1 + \frac{\sigma}{\epsilon \omega}} + 1)} \\
\beta &= \omega \sqrt{\frac{\mu \epsilon}{2} (\sqrt{1 + \frac{\sigma}{\epsilon \omega}} - 1)}
\end{align*}$$

(3)

The solution to the wave equations for waves propagating vertically downwards (1D medium) can then be written as:

$$\begin{align*}
\vec{E} &= \vec{E}_0 e^{-i \gamma z} e^{i \omega t} \\
\vec{H} &= \vec{H}_0 e^{-i \gamma z} e^{i \omega t}
\end{align*}$$

(4)

Where $\vec{H}_0$ and $\vec{E}_0$ are the magnetic and electric field strengths at a reference point $z=0$.

The far field horizontal components for a n-layered earth they are defined as:

$$\begin{align*}
E_{jx} &= E_{jx}^+ e^{-ik_j z} + E_{jx}^- e^{ik_j z} \\
H_{jy} &= \frac{E_{jy}^+}{\eta_j} e^{-ik_j z} + \frac{E_{jy}^-}{\eta_j} e^{ik_j z}
\end{align*}$$

(5)

where the subscript $j$ denotes a layer of the n-layered earth and $\eta$ is the intrinsic impedance. Now to correlate these two fields a concept called impedance is used. The definition of the wave impedance tensor is given by:

$$\vec{Z} = \vec{E} \ast \vec{H}^{-1}$$

(6)

Now extending impedance into 3D models we can write equation 6 as a tensor equation:

$$
\begin{bmatrix}
E_x \\
E_y \\
E_z
\end{bmatrix} =
\begin{bmatrix}
Z_{xx} & Z_{xy} & Z_{xz} \\
Z_{yx} & Z_{yy} & Z_{yz} \\
Z_{zx} & Z_{zy} & Z_{zz}
\end{bmatrix}
\begin{bmatrix}
H_x \\
H_y \\
H_z
\end{bmatrix}
$$

(7)

At the earth’s surface the $E_z$ component is very small compared to the other components hence, equation 7 can be written for the horizontal components as:

$$\begin{align*}
E_x &= Z_{xx} H_x + Z_{xy} H_y \\
E_y &= Z_{yx} H_x + Z_{yy} H_y
\end{align*}$$

(8)
The equations from 8 are the central equations used in CSAMT and can be used to solve for resistivities. But to gain even better models further quantities can be calculated, one of these is the vertical magnetic transfer function, also called the "Tipper". This is gained by first expressing the Z-component of the H-field as a function of horizontal components:

$$H_z = T_x H_x + T_y H_y = T \cdot H_{\text{horizontal}}$$  \hspace{1cm} (9)

Solving equation 9 for T gives:

$$\vec{T} = \vec{H}_z * \vec{H}_z^{-1}_{\text{horizontal}}$$

the Tipper is representative of the tilt of the magnetic fields or direction through the horizontal XY-plane.

Using equation 8, one can approximate the Cagniard or apparent resistivity as:

$$\rho_{ij} = \frac{1}{\omega \mu_0 |Z_{ij}|^2} [\Omega \cdot m]$$  \hspace{1cm} (10)

The phase of the resistivities is then:

$$\Phi_{\rho_{ij}} = \text{Arg}(Z_{ij})$$  \hspace{1cm} (11)

Where Arg is the principal argument function. The CSAMT method will have an effective penetration, this is commonly described by "Skin depth $\delta$". At depths greater than the skin depth signal strength is reduced by a factor $\frac{1}{e}$. The skin depth is defined as:

$$\delta = \sqrt{\frac{2}{\omega \mu \sigma}} \approx 503 \sqrt{\rho T}$$  \hspace{1cm} (12)

where $\rho$ is the electric resistivity of the media and $T$ is the period of the signal. Further when conducting CSAMT measurements the signal strength cannot be allowed to become to weak, as this would severely hinder analysis. Thus there exists a quantity $D$ called the investigation depth, $D$ for a specific skin depth $\delta$ is approximately:

$$D = \frac{\delta}{\sqrt{2}} \approx 356 \sqrt{\rho T}$$  \hspace{1cm} (13)

depending on data quality and geological structure. CSAMT using a relatively low frequency band is most effective for exploration depths of 100 meters to 4 km from the surface.

To fully determine these equations the survey in question must be of the tensor CSAMT type, where $(E_x, E_y, H_x, H_y, H_z)$ are all measured with at least two different polarisations. During the measurements the EM components are measured as a time series, resulting in the above equations all being solved for spectral values or sets of values. This complicates the equations somewhat but they are still solved the same way, described in detail by Sims et al. (1971). If instead only a lower dimension model is required a scalar CSAMT measurement can be conducted measuring $(E_x, E_y, H_x, H_y, H_z)$ using only one source polarisation.
2.2 CSAMT measurement work flow

CSAMT measurements (at Uppsala University) are done via first placing a transmitter with dipoles placed in two orthogonal directions (can be placed in any two direction orthogonal to each other (Figure 1), choosing cardinal direction simplifies the placement of both transmitter and receivers). Thereafter a receiver line is placed, with receiver sites placed as evenly as the terrain allows along the direction of interest. These receiver sites use five electrodes placed in the directions specified by the transmitter and one at a central point, as well as three induction coils placed along the two directions and one coil vertically (up-down). These measures the electric and magnetic fields continuously at a given sampling rate and log the data in an internal storage.

![Figure 1: Example of 3D CSAMT station setup. Figure from Zonge & J. Hughes (1991)](image)

During measurements the transmitter sends a square wave signal at the desired frequency for a set amount of periods, and all stations record continuously. When the whole frequency table has been recorded the processing starts (flowchart in Figure 2). Firstly as the recorded data is in a continuous block, the parts for each frequency is extracted using logged times from the transmission. Now each of these segments are handled separately as they correspond to different transmission frequencies. The data is then tapered at the ends to avoid spectral leakage caused by the fft. Then the filtering and trend removal is done to further reduce the noise. To compute the transfer functions \((Z \text{ and } T)\) the spectra of all electromagnetic field components are needed.

This is done both for the full time series as well as for segments of the original series to allow for calculation of errors. The data is Fourier transformed using fast Fourier transform and the spectra of all electromagnetic field components are extracted. Then, to calculate the spectra for each segment the data is simply segmented before the fft, whereafter the spectra for each segment is calculated. The data is also corrected for system responses using calibration data for the employed electric and magnetic field sensors.
Using these spectra the transfer functions and its errors are calculated using either a remote reference method or a single site method.

Figure 2: Flowchart of CSAMT data processing.

2.3 Drift removal & filtering

In time series analysis, one of the most prominent concepts is the one about filtering or windowing. This is often done to reduce the noise from a given time signal where noise in this case refers to the unimportant parts of the signal. These parts mostly consist of frequencies far outside the range of the measured phenomena or as known noise frequencies from other more or less well understood sources. For this chapter Roberts (2018) and Kanasewich (1981) have been used as sources. The simplest filter is the boxcar filter (Figure 3) which can be defined:
\[
\begin{align*}
H(t) &= 1 : t \in \left[-\frac{T}{2}, \frac{T}{2}\right] \\
H(t) &= 0 : \text{otherwise}.
\end{align*}
\]

A Boxcar window with its impulse response

Figure 3: A Boxcar window with its impulse response, notice the ringing at both sides of the time vector.

This filter is the absolutely simplest filter which cuts the signal into a smaller piece in the time domain or works as a pass band in the frequency domain. Filters used in the frequency domain also have what is called an impulse response. This is the signal which corresponds to the inverse Fourier transform of the filter and thus how the filter interacts with a signal in the time domain. Remember that while the filtering is done via multiplication in the frequency domain, a convolution operation is needed in the time domain to reach the same result.

The Butterworth filter (Figure 4) is a useful filter as it is variable with both desired cut-off frequency and the order of the filter. The filter is defined as:

\[
\begin{align*}
H^2(\omega) &= \frac{1}{1+(\frac{\omega_b}{\omega_c})^{2N}} : \text{for band pass} \\
H^2(\omega) &= \frac{1}{1+(\frac{\omega}{\omega_c})^{2N}} : \text{for low pass} \\
H^2(\omega) &= 1 - \frac{1}{1+(\frac{\omega}{\omega_c})^{2N}} : \text{for high pass}
\end{align*}
\]

Where \(\omega\) is the frequency and \(\omega_c\) and \(\omega_b\) are the cutoff-frequency and the centre-frequency respectively. The order \(N\) of the Butterworth increases the steepness towards the cutoff frequency and if we let \(N \to \infty\) the filter will go towards a boxcar. With this, there is a rapid increase in ripples in the impulse response to the filter, thus a suitable order of the filter will yield rapid cutoff and not to strong ringing in the time domain.
Butterworth filters with N=[2,6,20] and their impulse responses.

Figure 4: Comparison between different types of Butterworth filters with different N values and their impulse responses. Notice the decrease in amplitude but increased "ringing" in the impulse response with increasing N

Further we have filters which removes known noise frequencies and their multiples, called notch filters (Figure 5). These filters "notch" out the known noise frequencies and can be defined as:

\[
\begin{align*}
H(\omega) &= 0 : \omega \in [\omega_{\text{noise}} - \epsilon, \omega_{\text{noise}} + \epsilon] \\
H(\omega) &= (0, 1) : \omega \in [\omega_{\text{noise}} - \epsilon - \delta, \omega_{\text{noise}} + \epsilon + \delta] \\
H(\omega) &= 1 : \text{otherwise}
\end{align*}
\]

where $\omega_{\text{noise}}$ is a known unwanted frequency and $\epsilon$ and $\delta$ determines how wide the notch is. The reason that the filter is not simply zero or one in the whole interval is to reduce spectral leakage. Instead of instantaneously changing the values to 0 they are quickly tapered to 0 with the use of an exponential or a cosine bell function. Multiplying with a notch filter in the frequency domain simply removes all known noise contributions thus making the rest of the data much easier to analyse.
Filters can be of two types: finite impulse response (FIR) or infinite impulse response (IIR). This only depends on whether or not the filters’ corresponding time domain impulse response is of finite or infinite length. For a FIR, the impulse response reaches 0 for a finite time and then stays at 0. An IIR can have its amplitude approach zero but will never truly reach zero for any finite time. This has some large implications in computer science, but here we only note that the filters used in this project are of the IIR type.

There is a lot to gain by filtering the data in the time domain, both in terms of data quality and in technical capabilities. To filter in time domain, the filters’ transfer function has to be extracted from the frequency domain. The transfer function is the function describing the filters’ impact on a given signal, and is described by a number of filter coefficients. Using these coefficients, it is possible to filter in the time domain by either solving a system of differential equations or by performing a convolution operation. In this project, the filtering was done via solving a system of differential equations using Matlab’s filter function, see The MathWorks (2006) for full documentation.

The gains from filtering in the time domain are both to be able to handle lower frequencies and to be able to handle data without risking spectral leakage when using the Fourier transform. The use of detrending is further discussed by Liu et al. (2019) who discuss different methods to detrend EM data. The method discussed uses stacking and several wave packages to detrend low frequency signals and shows the strength of detrending.

### 2.4 Signal coherency

In time series analysis, one very important property is signal coherency. Coherency is used widely within the EM field of geophysics and its correlation to data quality is a valuable asset in data processing as seen and argued for by Gehrmann et al. (2019). In frequency domain, coherency can be defined by different expressions but most generally
it is defined as:

\[ Coh(Z_k, X_k) = \frac{1}{2m+1} \sum_{l=k-m}^{k+m} \frac{Z_lX_l^*}{\sqrt{(Z_l Z_l^*)(X_l X_l^*)}} \]  

(14)

Here, \( Coh(Z_k, X_k) \) is the coherence between two channels \( Z \) and \( X \) with the same length, at a specific centre frequency given by the central value \( k \). \( X^* \) and \( Z^* \) are both complex conjugates of the respective values and \( m \) is the number of frequencies on each side of the point \( k \).

To visualise the coherency one can look at it geometrically, firstly it is clear that because of the square root within the sum all values are normalised, to a value between 0 and 1 \( \| Z_l X_l^* \| \in [0,1] \). Both \( X_l^* \) and \( Z_l^* \) are complex values and can be represented as points on the unit circle in the complex plane (Figure 6 and 7). If these points are represented by vector then the sum means adding these vectors into a new complex vector with a length \( l \leq 2m+1 \). Dividing this vector norm by \( 2m+1 \) gives a number between 0 and 1 which is the coherency (Figure 8).

Figure 6: Illustration showing the \( X, Z, ZX^* \) (red, blue and green) vectors. Here the signals show low coherence and both \( X \) and \( Z \) are completely random vectors.
Figure 7: Illustration showing the \( X, Z, ZX^* \) (red, blue and green) vectors. Here the signals show high coherence and both \( X \) and \( Z \) are completely random vectors.

Figure 8: Coherency vector summation for \( ZX^* \) vectors from figure 6. The norm of the vector is directly related to coherency by \( \text{Coh}(Z, X) = \frac{|| \sum ZX^* ||}{m} \).
2.5 Transients in time series

During long time series measurements, it is to be expected that some data points will be contaminated by external noise. These data points might be the results of mechanic inputs at the measurement points due to animals or wind motion translated through the roots of trees, they might also be of less quality because of transient electrical signals in the measurement equipment, caused by abrupt electrical load changes in infrastructure, pulsed cattle fences, etc. The end result is a decrease in data quality and thus making the spectra noisier. One of these problems is caused by transients in the time series (Figure 9). A transient is a data spike (i.e. a sharply increasing/decreasing data value) that then decreases rapidly over the next couple of data points.

These transients drastically decreases data quality as they carry a large amount of distinct frequencies, thus increasing the background noise of the spectra. This in turn makes the desired amplitudes of the carrier frequencies much harder to distinguish from the background noise. One simple way to possibly reduce the effect of these transients is to simply remove them, by tapering to to zero or the average background signal (Figures 10 and 11). Yet when removing data one has to be extremely careful to not introduce bias, i.e. one has to be completely sure that the removed data is an experimental error from the measurement.

![Example of data contaminated by transients](image)

Figure 9: Example of a simple data set with 4 distinct transients with amplitude grater then 10.
Figure 10: Example to show the effect of simply tapering out transients from the time series shown in Figure 9.

Figure 11: Effect of frequency spectrum of the same signals as Figure 10. Notice that by tapering away the transients we come closer to the spectrum of the original signal.

Some transients are easily detected and deleted, because the amplitude of the signal sharply increases with a factor 100 in a specific spot, whereas in neighbouring time segments the signal follows a consistent pattern.
If these transients were identified, one could then replace them with the mean value of the time-series (either the mean of a neighbouring part of the time series or the mean of the entire series). This should reduce the amount of spectral noise, especially when the difference between the expected value and the transient is larger than the difference between the expected value and the mean.

To identify these transients long and short moving mean values can be computed for each field component and segment, then by division a ratio \( R \) can be determined for each point. This \( R \) should exhibit distinct peak values specifically over the areas contaminated with transients. To use this method for each value \( X_j \) in the time series \( X \), the long and short moving mean values \( L \) and \( S \) are defined as:

\[
L_j = \frac{1}{2*l+1} \sum_{i=j-l}^{j+l} f_i^2
\]  
(15)

\[
S_j = \frac{1}{2*s+1} \sum_{i=j-s}^{j+s} f_i^2
\]  
(16)

where: \( s \) and \( l \) and determine the lengths of the short and long window respectively. The ratio \( R \) is then calculated as:

\[
R_j = \frac{S_j}{L_j}
\]  
(17)

If the short window \( S \) contains approximately one period of the signal whereas \( L \) contains a multitude, \( L \) will be semi constant as the mean value of the signal. \( S \) on the other hand will drastically change if a transient is located within the window. Thus without a data transient in the data, \( R \) will tend to 1. In contrast if there exists a large data transient, \( R \) will increase above 1. Then by using a simple threshold value the transient positions can be determined whereafter they are tapered out using a tapered cosine notch window Bastani (2001).

3 Method

The project method can be clearly divided into three different processes increasing the data quality: implementing the drift removal in time-domain, creating and implementing the coherency test and lastly to identify transients and taper them out.

3.1 Drift removal in time domain

For each measured component as well as polarisation, a 6’th order Butterworth high-pass filter and a notch filter is created in frequency domain. Using Matlab’s inherent filter function the data is first filtered in the time domain using the generated Butterworth filter coefficients. Thereafter the data is Fourier transformed and the notch filter is applied in frequency domain. The notch filter is created based on two known noise frequencies (16 Hz and 50 Hz) and their multiples contained in the frequency spectra. After the data has been filtered, the SN ratio is measured according to:

\[
SN = \frac{\text{magnitude at current transmitter frequency}}{\text{median (power spectra)}}
\]  
(18)
where the magnitude at the current transmitter frequency is approximated using linear interpolation if the frequency lies between numerically represented frequencies (as the spectral resolution is good and the sending frequencies are on whole numbers this should not be a problem).

### 3.2 Signal coherency test

The desired coherency is the coherency between the measured electric field components $E_x$ and $E_y$ and the predicted electric field components calculated using $H_x$ and $H_y$ and the predicted impedance tensor $Z$. This prediction coherency should be calculated for each segment and each frequency. Therefore after a time series has been divided into the desired number of segments a coherency value should be calculated for each segment to find bad segments that then can be discarded. The coherence value can be approximated with the expression:

$$
\gamma^2_{E_x,E_{x-pred}} = 1 - \frac{(E_x - (Z_{xx} * H_x + Z_{xy} * H_y))(E_x - (Z_{xx} * H_x + Z_{xy} * H_y))^*}{|E_x|^2} 
$$

(19)

$$
\gamma^2_{E_y,E_{y-pred}} = 1 - \frac{(E_y - (Z_{yx} * H_x + Z_{yy} * H_y))(E_y - (Z_{yx} * H_x + Z_{yy} * H_y))^*}{|E_y|^2} 
$$

(20)

Here all components of $Z$ are to be calculated using data from a single segment and the same segment for close frequencies. This expression approaches 1 as the coherence approaches 1 but at low coherency $\gamma^2$ can take on negative numbers. This may not be a problem whenever the CSAMT signal is strong. Further, if the ambient noise is only episodic, the related noise contaminated segments can be removed using coherence thresholds. The next problem lies in the fact that for each segment of the time series only one spectral value for $E$ and $H$ can be determined, thus $Z$ is retrieved from an even determined inversion problem, leading to a constant coherency of 1 for all segments. This in turn can be solved by computing coherence as a sum over sets of neighbouring frequencies (bandwidth $2m + 1$ as in equation 14). Here the impedance tensor elements are computed for the given frequency band rather than the centre frequency or mid residual frequencies, making the inversion problem over-determined. After $\gamma^2$ values are computed threshold is used to remove any segment with a lower $\gamma^2$ value. These segments and their respective segment for the other polarisation is then discarded and the rest of the data processing is continued with the more robust segments.

### 3.3 Transient detection and removal

To remove the transients from the time series with a specific transmitter frequency (10 Hz as an example) it is important to handle all components equally. The goal is to not disturb the known relations between components and the impedance tensor. Thus firstly the long and short window method is used on each component ($E_x, E_y, H_x, H_y, H_z$) to calculate their respective R-ratios. The R-ratio is then subdivided into a number of segments and a threshold of 5 medians of the segment is chosen. These thresholds are then combined to a variable threshold for the whole R-ratio.

All R-values exceeding this threshold are deemed as transients and their positions are recorded. Adding all of these positions for each component of a specified frequency
together, we find the position of all suspected transients over all 5 components. Thereafter all points within a specified number of points are deemed transients, and a cosine taper is placed over each of these transient areas. This filter is then applied to each of the respective time series individually. The filter either tapers the values of the points to 0 or to the mean value of the complete time series if the series contains an offset not yet filtered out.

4 Results

The results are given for each of the methods described in the method. As small improvements in signal quality is hard to quantize most of the results are given in ratios, either between signal and noise strength (SN ratios) or as ratios between these ratios to easily see if the change is positive or negative.

4.1 Drift removal in time domain

Using drift removal in time domain the SN ratio of the data stayed approximately the same. Typically the differences were below 1%. This is mostly because there are no pronounced trends to remove except for constant offsets of the respective fields. To check the viability of the time domain trend removal the method was tested when an artificial linear trend was added to the data. This in turn made the SN ratio of the time domain removal slightly superior to the frequency counterpart for all but the lowest transmitter frequencies (Figure 12 and Table 1).

![Figure 12: Plot showing the fraction $\frac{SN_{\text{time domain}}}{SN_{\text{frequency domain}}}$ both before and after adding a linear trend. Thus a value above 1 indicates an improvement when implementing time domain detrending and a value below 1 indicates a deterioration. The data presented is from station 1. Notice that most discrepancies are observed at the lower transmitter frequencies. (d.u. stands for dimensionless unit.)](image-url)
### Table 1: Data from Figure 12

<table>
<thead>
<tr>
<th>Data</th>
<th>Without trend</th>
<th>With trend</th>
</tr>
</thead>
<tbody>
<tr>
<td># of points with positive change</td>
<td>(47/112)</td>
<td>(83/112)</td>
</tr>
<tr>
<td># of points with &lt; 1% change</td>
<td>(103/112)</td>
<td>(63/112)</td>
</tr>
<tr>
<td># of points with &gt; 1% positive change</td>
<td>(5/112)</td>
<td>(38/112)</td>
</tr>
<tr>
<td># of points with &gt; 1% negative change</td>
<td>(4/112)</td>
<td>(11/112)</td>
</tr>
</tbody>
</table>

Table 1: Data from Figure 12. Total number of SN ratios for the filtering process are 112, 14 of each component divided into 2 polarisations for each of the methods. Notice that without the trend almost all points (103/112) where almost unchanged whereas with a trend present only 68 points were relatively unchanged.

### 4.2 Signal coherency test

After some testing using the developed coherence test, the measured frequency band is too sparse to be able to construct a meaningful coherency test, combining summation over a given frequency band as in equation 14 and impedance based coherency as in equations 19 and 20. Therefore it was decided to not implement a coherency test in the scope of this project.

### 4.3 Transient removal

Using the developed transient removal method most of the larger transients where removed. Yet some of the minor transients still remain and the method generated some additional artefacts. The signal to noise ratio for the transmitter frequencies was numerically larger but overall almost unchanged. Lastly as there are a lot of data to apply the transient removal method to, only one example is presented in Figures 13 to 16 and table 2. It was also noted that some transients seems to not have been completely tapered away, instead some of the tail remains (Figure 14, panel 3)
Figure 13: Example of $E_x$ time series before transient removal, for one specific station and at a sending frequency at 80 Hz. The third panel is a zoomed in picture of the largest transient.

Figure 14: $E_x$ from Figure 13 time series after transient removal where black stars indicate located and removed transients. The third panel is a zoomed in picture of the largest transient. Notice that even though there is still visible transients in the filtered spectrum the amplitudes of the remaining transients have been lowered.
Figure 15: Original frequency spectrum before transient removal. Spectrum of one component \( E_x \) for one station at one frequency (80 Hz).

Figure 16: Frequency spectrum after transient removal. Spectrum of one component \( E_x \) for one station at one frequency (80 Hz).
Without transient removal & With transient removal \\
Amplitude of 80 Hz peak (d.u.) & $4.019 \times 10^4$ & $4.203 \times 10^4$ \\
Largest close noise of 80 Hz peak (d.u.) & 4554 & 5243 \\
Peak at 80Hz (d.u.) & 8.825 & 8.016 \\
Amplitude of 240 Hz peak (d.u.) & $2.739 \times 10^4$ & $2.709 \times 10^4$ \\
Largest close noise of 240 Hz peak (d.u.) & 24078 & 24424 \\
Peak at 240Hz (d.u.) & 8.270 & 10.161 \\
Amplitude of 560 Hz peak (d.u.) & $1.023 \times 10^4$ & $1.094 \times 10^4$ \\
Largest close noise of 560 Hz peak (d.u.) & 2533 & 1953 \\
Peak at 560Hz (d.u.) & 4.039 & 5.601 \\

Table 2: Comparison of data for three multiples of the sending frequencies 80, 240 and 560 Hz from Figures 15 and 16. With close noise a interval of ± 1Hz is used

4.4 Effect on transfer functions

Finally there is the effect of the whole method on the resulting transfer functions, resistivities and phases. The effect here can mostly be measured in the change in the magnitude of errors as well as how closely the different methods corresponds. The effect on the transfer functions is minimal as can be seen in figures 17 to 20, but when further examined the difference in magnitude and errors can be observed (Tables 3 and 4).

![Figure 17](image-url)
Figure 18: Transfer functions, resistivities and phases for station 1 after processing with time domain detrending and transient removal. Remote reference in blue, single site in red and entire time-series processing results in yellow.

Figure 19: Four components of the original transfer functions, resistivities and phases for station 1 without the use of time domain detrending and transient removal. Remote reference in blue, single site in red and entire time-series processing results in yellow.
Figure 20: Four components of the transfer functions, resistivities and phases for station 1 after processing with time domain detrending and transient removal. Remote reference in blue, single site in red and entire time-series processing results in yellow.

Table 3: Data comparison of $Re(Z_{yx})$ for Figures 19 and 20. RR, SS and ET stands for remote reference, single site and entire time series processing respectively.

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>10Hz</th>
<th>20Hz</th>
<th>56Hz</th>
<th>224Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original $Re(Z_{yx})[\frac{V}{A}]$ (RR)</td>
<td>0.858±0.018</td>
<td>0.2369±10$^{-18}$</td>
<td>-2.342±10$^{-18}$</td>
<td>-12.24±0</td>
</tr>
<tr>
<td>$Re(Z_{yx})[\frac{V}{A}]$ after changes. (RR)</td>
<td>0.855±0.036</td>
<td>0.261±10$^{-20}$</td>
<td>-2.205±0</td>
<td>-12.18±0</td>
</tr>
<tr>
<td>Original $Re(Z_{yx})[\frac{V}{A}]$ (SS)</td>
<td>0.8222±0.043</td>
<td>0.1191±0.152</td>
<td>-2.366±0.119</td>
<td>-12.17±0.086</td>
</tr>
<tr>
<td>$Re(Z_{yx})[\frac{V}{A}]$ after changes. (SS)</td>
<td>0.813±0.0527</td>
<td>0.130±0.1496</td>
<td>-2.224±0.134</td>
<td>-12.26±0.0865</td>
</tr>
<tr>
<td>Original $Re(Z_{yx})[\frac{V}{A}]$ (ET)</td>
<td>0.8413</td>
<td>0.2105</td>
<td>-2.37</td>
<td>-12.25</td>
</tr>
<tr>
<td>$Re(Z_{yx})[\frac{V}{A}]$ after changes. (ET)</td>
<td>0.8491</td>
<td>0.2075</td>
<td>-2.202</td>
<td>-12.26</td>
</tr>
</tbody>
</table>

Table 4: Data comparison of $Im(Z_{yx})$ for Figure 19 and 20. RR, SS and ET stands for remote reference, single site and entire time series processing respectively.

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>10Hz</th>
<th>20Hz</th>
<th>56Hz</th>
<th>224Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original $Im(Z_{yx})[\frac{V}{A}]$ (RR)</td>
<td>-1.072±0.018</td>
<td>-2.578±10$^{-18}$</td>
<td>-6.45±10$^{-18}$</td>
<td>-8.425±0</td>
</tr>
<tr>
<td>$Im(Z_{yx})[\frac{V}{A}]$ after changes. (RR)</td>
<td>-1.022±0.0356</td>
<td>-2.428±10$^{-19}$</td>
<td>-6.309±0</td>
<td>-8.402±0</td>
</tr>
<tr>
<td>Original $Im(Z_{yx})[\frac{V}{A}]$ (SS)</td>
<td>-1.079±0.043</td>
<td>-2.616±0.152</td>
<td>-6.354±0.119</td>
<td>-8.354±0.0862</td>
</tr>
<tr>
<td>$Im(Z_{yx})[\frac{V}{A}]$ after changes. (SS)</td>
<td>-1.021±0.0527</td>
<td>-2.436±0.150</td>
<td>-6.15±0.134</td>
<td>-8.336±0.087</td>
</tr>
<tr>
<td>Original $Im(Z_{yx})[\frac{V}{A}]$ (ET)</td>
<td>-1.083</td>
<td>-2.555</td>
<td>-6.309</td>
<td>-8.442</td>
</tr>
<tr>
<td>$Im(Z_{yx})[\frac{V}{A}]$ after changes. (ET)</td>
<td>-1.034</td>
<td>-2.477</td>
<td>-6.368</td>
<td>-8.429</td>
</tr>
</tbody>
</table>
5 Discussion

5.1 SN-ratio from drift removal

The method of drift removal in time domain clearly works as intended, yet on the data used during this project the gain from using it is negligible. As the data does not contain any major trends the SN ratio is almost unchanged. Relative to the original frequency domain detrending, the changes of the SN ratio are in the range of 0.1 to 5 (Figure 12). Where values larger then one indicates an improvement. Hence at some signal frequencies \( f \geq ? \) there is an improvement in SN ratio whereas for lower frequencies the SN ratio deteriorates.

Yet the cost of this improvement is as always time. Even though a full time series convolution is not needed to do the detrending, a large matrix equation needs to be solved. This equation is in principle a set of equations equal to the number of coefficients from the transfer function of the high-pass filter for each point in the time series. So even tough a Butterworth filter in this case only has 7 transfer coefficients, there is a lot of data points. Yet these operations though numerous are quite simple so the time lost is not deal breaking but it is noticeably longer than the simple multiplication that is normally done in the frequency domain.

Another problem with this type of detrending is discussed by San Filipo & Hohmann (1983). This is the problem with lower frequencies when we rely on removing them by high-pass filters to remove any trends. In the data used for this project there are no "low" enough sending frequencies but there is nothing stopping one to do measurements using these frequencies. It is clear to see that when a strong trend is attached to the data we lose signal power in the lower frequencies. With that there might appear problems, but these are beyond the scope of this project but could be improved using different methods of detrending as discussed in Liu et al. (2019).

Thus, it might be preferred to manually check whether or not the data contains any noticeable trends and then to choose which type of detrending is to be done. Otherwise if the amount of time lost is not the highest concern, the time domain trend removal should be used, as it theoretically improves the processing by reducing spectral leakage if there are trends present, otherwise the type of detrending chosen seems interchangeable.

5.2 Limitations of the standard EM coherency model

Even though this coherency method did not work out in the end, there still exists a need for some kind of coherency model for the segmented data. The type of coherency used in this project comes from other EM data analysis where measured frequencies are in close proximity to one another. In CSAMT a logarithmic frequencies table is used, so none of the neighbouring frequencies are sufficiently proximate. This in turn makes the method of using close frequencies as a comparison unsuitable for the purpose as the responses may be too different to give any meaning.

One idea to implement some kind of coherency is to instead of using close frequencies to calculate the predicted impedance tensor. Maybe using neighbouring time-series segments or even sub-divide each segment further. This in turn has its own set of problems. Mostly that neighbouring segments that could be considered "bad" might affect the "good" segments and vice-versa. This further complicates the whole goal of the coherence process, which is to remove bad segments. Another idea is to use multiples of the transmitter frequency and use these to predict the impedance tensor and thus calculate the coherence.
these methods are something to be investigated further but that is beyond the scope of this project.

5.3 Tapering of transients

Overall, removing the transients from the time series seems to improve the initial time series data quality. Though it also is highly dependant upon the data itself. It is relatively easy to see that removing the absolutely largest and most noticeable transients improves the data but the problem lies in the smaller transients.

As most of the transients lie on local maximas and minimas of the time series, tapering them to zero creates a notch with the depth/height of the same magnitude as the series amplitude. This new notch can be seen as almost a new transient as it entails a abrupt change of data values.

Here the tightrope walking starts, should a more forgiving threshold be used and thus leaving more "transients" or should a harsher one be used maximising the amount of transients found? This is further complicated by the time-series, as they sometimes change amplitude and thus might give false indications to the long-short filter method. This in turn leads to the removal of "good" data which is not good at all, as one must always be careful when removing data to avoid any statistical bias.

The effect on the frequency spectra after implementation of the transient notching method shows that we increase signal to noise ratio. Yet this change is relatively small and for some values (most notable the first multiple) the ratio between the signal at the desired frequency and noise is reduced. This could be seen as a decrease in signal accuracy and is not desired.

All of these problems originate from the fact that the method used could be seen as somewhat simple, i.e. by simply tapering transients to zero the fact that this is not expected behaviour is disregarded. One thing that maybe could be done to improve the process of transient removal is to replace the tapering by an artificially created signal using a robust method, e.g a MEM-signal (maximum entropy method). The MEM method predicts the missing piece of the time series using the unaffected ends on both sides of around the transient. This is discussed thoroughly by Fontes et al. (1988) and this method might solve a lot of the problems created by just tapering away the transients, since it instead creates a signal fitted to both ends of the transient removing all sharp data changes.

5.4 Changes in transfer functions

As can be seen, the results have not changed much even after applying these new methods to the processing. To summarise: Some values of the Z-components, resistivities and phase have changed somewhat. Errors have decreased for high frequencies and increased for the lowest. Overall the changes in both errors and magnitude are about $0 - 10\%$ which corresponds to the change from both transient removal and trend removal in the time domain.

6 Conclusions

As a conclusion it can be said that the methods used in this project may have improved the data quality slightly. None of the methods in question have drastically changed the
quality of the spectra, yet both of the implemented methods seems to have the potential to improve data quality. This improvement seems heavily dependent upon initial data quality as the time-domain detrending will have more of an impact if there are trends present. Likewise if more or stronger transients were present in the data the improvement from notching them away would further overshadow the drawbacks of the notch filter. As the reduction of transients and transient amplitudes would be much greater then the added artefacts. In the data used for this project, the methods which contributed most to the change in results is the transient removal. The time domain detrending demonstrated little difference from the frequency domain counterpart as the data lacked any noticeable trends. Lastly the processing of CSAMT data was slightly improved or unchanged by this project but there is always more that could be done, examples being: the implementation of a working coherence test and to change the method of removing transients to a more robust method.

7 Acknowledgements

I would like to thank my supervisor Thomas Kalscheuer for allowing me the opportunity to work with EM geophysics. I would also like to thank my subject reviewer Mehrdad Bastani for both the comments which helped me structuring the report in a cohesive fashion and for agreeing to be a subject reviewer on relatively short notice. I would also like to thank Julia Fridlund who has been working alongside me on other aspects of the CSAMT processing. Finally I would like to thank Lars Dynesius, Paula Rulff, Laura Schmidt, and Michael Weiss for the opportunity to partake in a CSAMT field measurement.

References


**URL:** https://se.mathworks.com/help/matlab/ref/filter.html

Appendices

Appendices A, B, C and D contain some of the Matlab functions used to carry out the methods discussed in the report. Appendix E contains the SN ratio data from station one, used when calculating and plotting Figure 12.
A Code to find R value

function \[R\] = FtestJF2(Data, s, l)

% FTESTJF – spike detection; slide short and long windows along the time series and calculate average values in windows.
% % S(k) = short time average around k, L(k) = long time average around k
% % If R(k) = S(k)/L(k) is large, there is a probable spike at time k.
% % Data: the time series
% % s: half-length of short window (total length 2s+1)
% % l: half-length of long window (total length 2l+1)
% % - originally written by Oskar, 2019-04-16
% % - modified by Julia, 2019-04-16

T = length(Data); % # of data samples
Data = Data - mean(Data); % remove average
Data2 = Data.^2; % data squared
S = zeros(1,T); % allocate array for S values
L = zeros(1,T); % allocate array for L values
S1 = sum(Data2(1:2*s+1))/(2*s+1); % S in start of time series
S2 = sum(Data2(T-2*s+1:T))/(2*s+1); % S in end of time series
L1 = sum(Data2(1:2*l+1))/(2*l+1); % L in start of time series
L2 = sum(Data2(T-2*l+1:T))/(2*l+1); % L in end of time series

% Short term average, S
S(1:s) = S1; % if short window reach start of time series
S(T-s+1:T) = S2; % if short window reach end of time series
S(s+1:T-s) = movmean(Data2, 2*s+1, 'Endpoints', 'discard'); % if short window inside time series

% Long term average, L
L(1:l) = L1; % if long window reach start of time series
L(T-l+1:T) = L2; % if long window reach end of time series
L(l+1:T-l) = movmean(Data2, 2*l+1, 'Endpoints', 'discard'); % if long window inside time series

% Ratio, R
R = S./L;

end
function [TOT, TransientI , data]=findTransient (R)

%findTransient tries to find all transients for data R
% Using the method:
% Firstly the data is segmented into NR segments and normalised.
% Then all data < 5*median of its respective segment is discarded.
% Then all data < 5*median of the remaining data in the segments is discarded
% thereafter the larger half of the remaining data is taken as the
% transients.
% R is data from long short window method applied on a time series.
% Much to improve.
% FTESTIF - spike detection; slide short and long windows along the time
% series and calculate average values in windows.
% Originally written by Oskar, 2019-01-16

T=length(R);
NR=20;                          % # of segments. might change
window=floor(T/NR);R=R-mean(R);% working with normalised data for easier calculations.
data=(R./max(R)).^2;

for k=0:NR-1
    Tr=zeros(1,window);
    Wdata=data(1+k*window:(1+k)*window);
    threshold1=5*median(Wdata);
    meanlim=Wdata>threshold1; % first mean threshold. might change
    if isempty(Wdata(meanlim))threshold2=0;
    else
        threshold2=5*median(Wdata(meanlim));
    end
    transients=Wdata>threshold1+threshold2;
    Tr(transients)=Wdata(transients);
end

for k=0:NR-1
    Transients(1+k*window:(1+k)*window)=Tr(k+1); % returning vector retaining size difference between R values.
end
TOT=ones(size(data));
for h=0:NR-1
    TOT(1+h*window:(1+h)*window)=Thr(h+1)*TOT(1+h*window:(1+h)*window);
end
TransientI=Transients~=0; % returning vector with only position of located transients

end
C  Code to create filters

function [ filter , b_BUTTER, a_BUTTER, NOTCH ] = Create_filter_CSAMT( 
    ProcPara, filter_lig_nrs, indp, indf, fi_freq, ff, ... 
    freq )

% Create_filter_CSAMT − creates the coefficients of the a butterworth filter as 
% well as a notch filter and the combination of these for 
% polarisation indp and frequency indf. 
% 
% Written by Jochen Kamm, Thomas Katscheuer and Oskar Rydman, 
% Uppsala University, Uppsala, Sweden 
%
% copy some processing parameters for faster access from structure 
% filter width, e.g. 0.005: sigma is half a percent of target frequency 
filter_width = ProcPara.filter_width ;
% extra wide filter for original noise tones (50 Hz and 16 2/3 Hz) 
filter_width_wide = ProcPara.filter_width_wide ;
% powerline and railway frequencies in Hz 
fp = ProcPara.fp ;
fr = ProcPara.fr ;
%
% initialise filter 
fil {indp} = ones(size(ff));
%
% notch filter for powerline and railway frequencies 
%
% loop over filter frequencies 
% skipping 3 in below list means skipping even multiples of 50 Hz 
for indfi = [6 5 4 2 1]
    if (indfi < 5) % only noise frequencies (5, 6 are transmitter frequencies, only for plotting) 
        for indii = 1 : numel(fi_freq{indfi}) 
            ftarget = fi_freq{indfi}(indii) ;
            if (ftarget == 0); continue; end
            fil {indp} = fil {indp}.*{(1−exp(−((ff−ftarget)/(ProcPara.filter_width*ftarget))."2))};
        end
    end
% KT OBS: better use delay filter (over two 
% periods) 
% first harmoninc filter a bit wider: 
fil {indp} = fil {indp}.*{(1−exp(−((ff−fp)/(filter_width_wide*fp))."2))};
fil {indp} = fil {indp}.*{(1−exp(−((ff+fp)/(filter_width_wide*fp))."2))};
fil {indp} = fil {indp}.*{(1−exp(−((ff−fr)/(filter_width_wide*fr))."2))};
fil {indp} = fil {indp}.*{(1−exp(−((ff+(fr))/filter_width_wide*fr))."2))};
end
%
% high−pass Butterworth filter 
%
% normalized corner frequency at 80 % of current Tx base frequency 
wn_butter = 0.8 * freq(indf)/(ProcPara.fs/2); 
% 6-th order filter 
N_butter = 6;
% compute HR coefficients of filter 
[b_butter, a_butter] = butter(N_butter, wn_butter, 'high');
%
% compute N-point complex frequency response vector H_butter 
[H_butter, w] = freqz(b_butter, a_butter, ff, ProcPara.fs);
if (ProcPara.plotit) 
    % plot Butterworth filter 
end
%
% update total frequency−domain filter 
filter = fil {indp}.*H_butter;

b_BUTTER = b_butter ;
a_BUTTER = a_butter ;
NOTCH = fil {indp} ;
end
D Code to filter time-series

function [SNbef, SNaft, fd] = Filter_CSAMT( timefilt, fil, b_BUTTER, a_BUTTER, NOTCH, fd, d, indp, ff, indf, nn)
% Filter_CSAMT − filters the data using the filter devised from
% Create_filter_CSAMT. If timefilt='true' then the data is first filtered
% in the timedomain via matlab filter function then the known noise
% frequencies are notched out in the freq domain. If timefilt='false', the
% whole operation is done in the freq domain. The SNratio of the used
% filtering is also returned.
%
% Written by Jochen Kamm, Thomas Kalscheuer and Oskar Rydman,
% Uppsala University, Uppsala, Sweden
%
if (timefilt == true)
    d_filtered = filter(b_BUTTER, a_BUTTER, d);
    fftd = fftshift(fft(d_filtered));
    SNbef = interp1(ff, abs(fftd), nn(indf,1)) ./ median(abs(fftd));
    fftd = NOTCH(indp).∗fftd;
    SNaft = interp1(ff, abs(fftd), nn(indf,1)) ./ median(abs(fftd));
    fd = fftd;
else
    SNbef = interp1(ff, abs(fd), nn(indf,1)) ./ median(abs(fd));
    fd = fil(indp).∗fd;
    SNaft = interp1(ff, abs(fd), nn(indf,1)) ./ median(abs(fd));
end
end
E Data used in calculating SN ratios for result

<table>
<thead>
<tr>
<th>freq [Hz]</th>
<th>Polariation</th>
<th>SN-Ratio $E_x$</th>
<th>SN-Ratio $E_y$</th>
<th>SN-Ratio $H_x$</th>
<th>SN-Ratio $H_y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
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<td>364.647</td>
<td>617.212</td>
<td>1159.711</td>
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<td>89.575</td>
<td>1985.153</td>
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<td>X</td>
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Table 5: SN-Ratios after the use of the created time domain detrending. The data is from one station in a measurement done in northern Sweden and all polarisation’s and transmitter frequencies are included. Notice that overall the Y-polarised transmissions have a lower SN ratio than their X-polarised counterparts.
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Table 6: SN-Ratios after standard frequency domain detrending. The data is from one station in a measurement done in northern Sweden and all polarisation’s and transmitter frequencies are included. Notice that overall the Y-polarised transmissions have a lower SN ratio than their X-polarised counterparts.
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<th>Change $E_x$ [%]</th>
<th>Change $E_y$ [%]</th>
<th>Change $H_x$ [%]</th>
<th>Change $H_y$ [%]</th>
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Table 7: Ratio of $\frac{SN_{time\text{filtered}}}{SN_{frequency\text{filtered}}}$ from data of table 1 and 2. A higher number represents an increase in SN ratio with the change to time-domain filtering and a 1 indicates no change to the third decimal. Any value lower than 1 indicates a loss of signal to noise ratio.
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<th>Change $H_x$ [%]</th>
<th>Change $H_y$ [%]</th>
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Table 8: SN-Ratios after the use of the created time domain detrending. The data is from one station in a measurement done in northern Sweden with an additional artificial linear trend. And all polarisation’s and transmitter frequencies are included. Notice that overall the Y-polarised transmissions have a lower SN ratio than their X-polarised counterparts.
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<th>Polarisation</th>
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<th>Change $E_y$ [%]</th>
<th>Change $H_x$ [%]</th>
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Table 9: SN-Ratios after standard frequency domain detrending. The data is from one station in a measurement done in northern Sweden with an additional artificial linear trend. And all polarisation’s and transmitter frequencies are included. Notice that overall the Y-polarised transmissions have a lower SN ratio than their X-polarised counterparts.
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Table 10: Ratio of \( \frac{SN_{time\text{-}filtered}}{SN_{frequency\text{-}filtered}} \) from data of table 4 and 5. A higher number represents an increase in SN ratio with the change to time-domain filtering and a 1 indicates no change to the third decimal. Any value lower than 1 indicates a loss of signal to noise ratio. Notice that overall the value is increased, yet the exception lies in the low frequencies, which seems to have worsened considerably.