

Seismic data interpolation using multichannel singular spectrum analysis

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INTRODUCTION



Why interpolation?

- It is very hard to design a seismic survey in a regular grid of sources and receivers because of economic restrictions on seismic data acquisition
- Missing traces producing sampling artifacts or noise during processing
- Many seismic processing tools for noise attenuation or imaging require high quality regularly sampled data to work properly



- Signal processing-based methods
 - The Fourier transform
 - The Radon transform
 - The Curvelet transform

- Wave-equation-based methods
 - Mapping and reconstruction operators
 - Finite difference offset continuation filter

- Rank reduction-based methods
 - Rank reduction of Hankel/Toeplitz matrix
 - For linear events



- Analysis of 1D time series
 - Study of climatic records
 - Signal reconstruction
 - Forecasting of time series
 - Filtering of digital terrain model
-
- ❖ In seismic data processing:
 - In frequency domain as rank reduction of the Hankel matrix
 - Random noise attenuation (Tricket, 2002. Sacchi, 2009)
 - Iterative algorithm for seismic interpolation (Oropeza and Sacchi, 2009)



THEORY



5 dimensions of a 3D seismic data:

➤ Vertical dimension

Time or depth for the vertical dimension

➤ Spatial directions

shot.x, shot.y, rcvr.x, rcvr.y (acquisition coordinates)

inline, crossline, offset, azimuth (processing coordinates)

cmp.x, cmp.y, offset.x, offset.y (processing coordinates)



Hankel matrix

Hankel Operator

$\{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9\}$

$$A_{i,j} = A_{i+k,j-k} \\ k = 0, 1, \dots, j-i$$

$$A = \begin{pmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \\ a_2 & a_3 & a_4 & a_5 & a_6 \\ a_3 & a_4 & a_5 & a_6 & a_7 \\ a_4 & a_5 & a_6 & a_7 & a_8 \\ a_5 & a_6 & a_7 & a_8 & a_9 \end{pmatrix}$$

Hankel matrix is:

- A square matrix with constant skew-diagonals from left to right
- Is closely related to Toeplitz matrix

Toeplitz matrix is:

- Diagonal constant matrix

Toeplitz Operator

$\{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9\}$

$$A_{i,j} = A_{i+1,j+1} = a_{i-j}$$

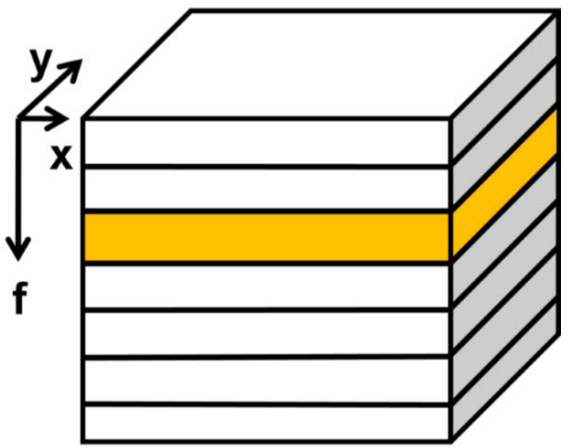
$$A = \begin{pmatrix} a_5 & a_4 & a_3 & a_2 & a_1 \\ a_6 & a_5 & a_4 & a_3 & a_2 \\ a_7 & a_6 & a_5 & a_4 & a_3 \\ a_8 & a_7 & a_6 & a_5 & a_4 \\ a_9 & a_8 & a_7 & a_6 & a_5 \end{pmatrix}$$

The rank reduction algorithm

$$s(x, y, t) = w(t - p_x x - p_y y)$$

$$s(x, y, \omega) = A(\omega) e^{-i\omega(p_x x + p_y y)}$$

Generating frequency slice for each frequency



$$S_\omega =$$

	y					
	$S(1,1)$	$S(1,2)$	$S(1,3)$...	$S(1, N_y - 1)$	$S(1, N_y)$
	$S(2,1)$	$S(2,2)$	$S(2,3)$...	$S(2, N_y - 1)$	$S(2, N_y)$
	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
	$S(N_x, 1)$	$S(N_x, 2)$	$S(N_x, 3)$...	$S(N_x, N_y - 1)$	$S(N_x, N_y)$
x						

Constructing one Hankel matrix for each inline



$$M_j =$$

$S(j, 1)$	$S(j, 2)$...	$S(j, K_x)$
$S(j, 2)$	$S(j, 3)$...	$S(j, K_x + 1)$
\vdots	\vdots	\ddots	\vdots
$S(j, L_x)$	$S(j, L_x + 1)$...	$S(j, N_x)$

$$M =$$

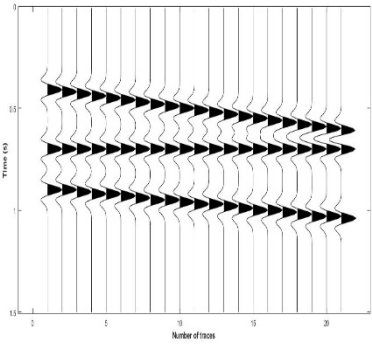
	M_1	M_2	...	M_{K_y}
	M_2	M_3	...	$M_{K_y + 1}$
	\vdots	\vdots	\ddots	\vdots
	M_{L_y}	$M_{L_y + 1}$...	M_{N_y}



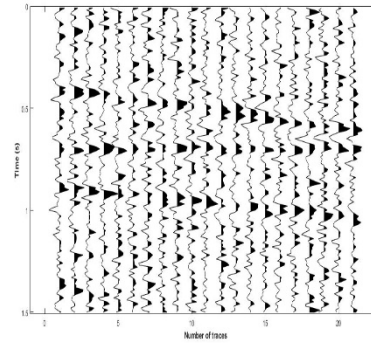
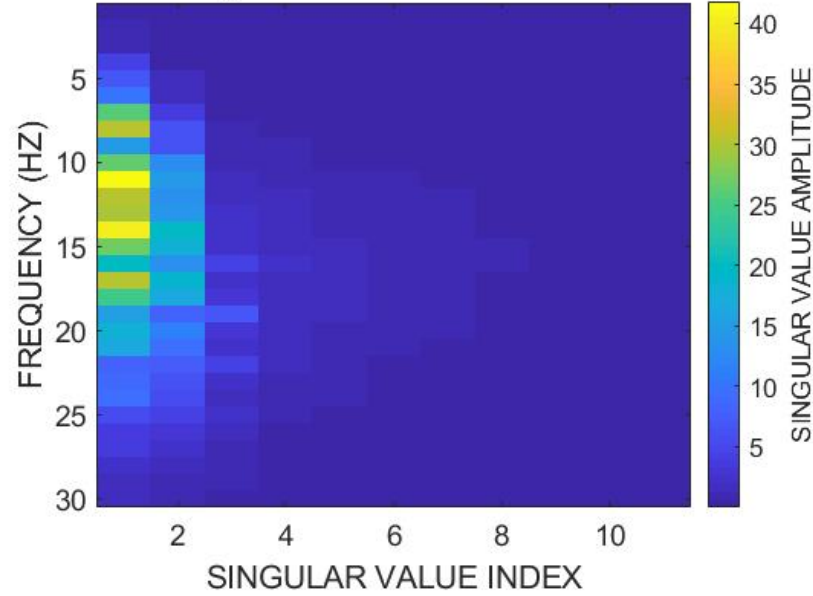
Making a Hankel of Hankel matrices



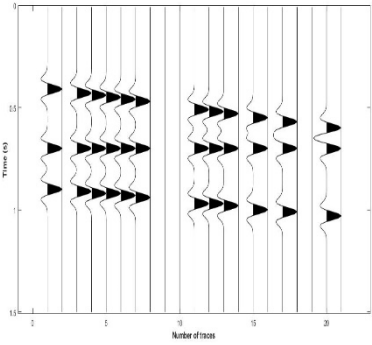
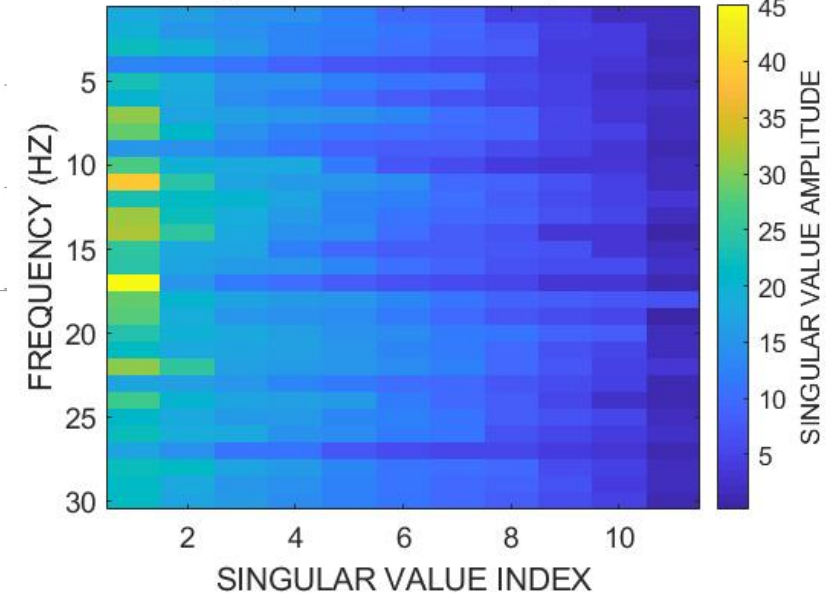
Theory of MSSA



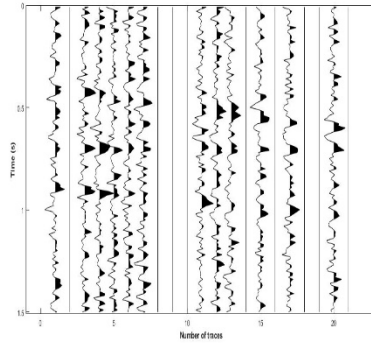
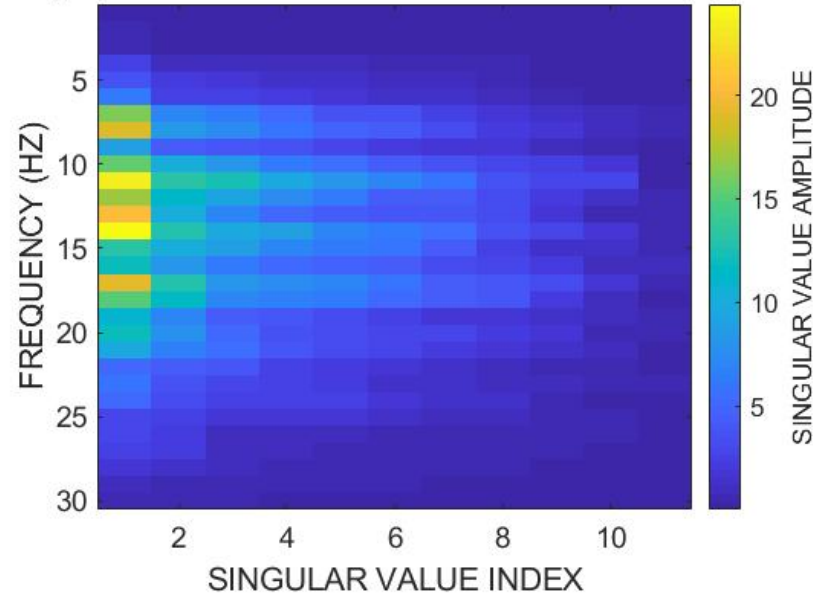
Singular values for clean data



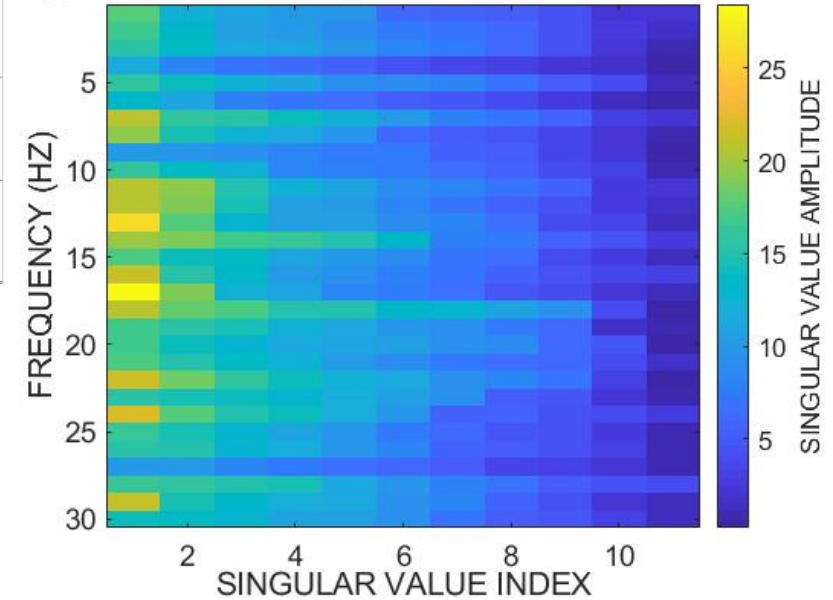
Singular values for noisy data



Singular values for clean data with 51% decimated traces

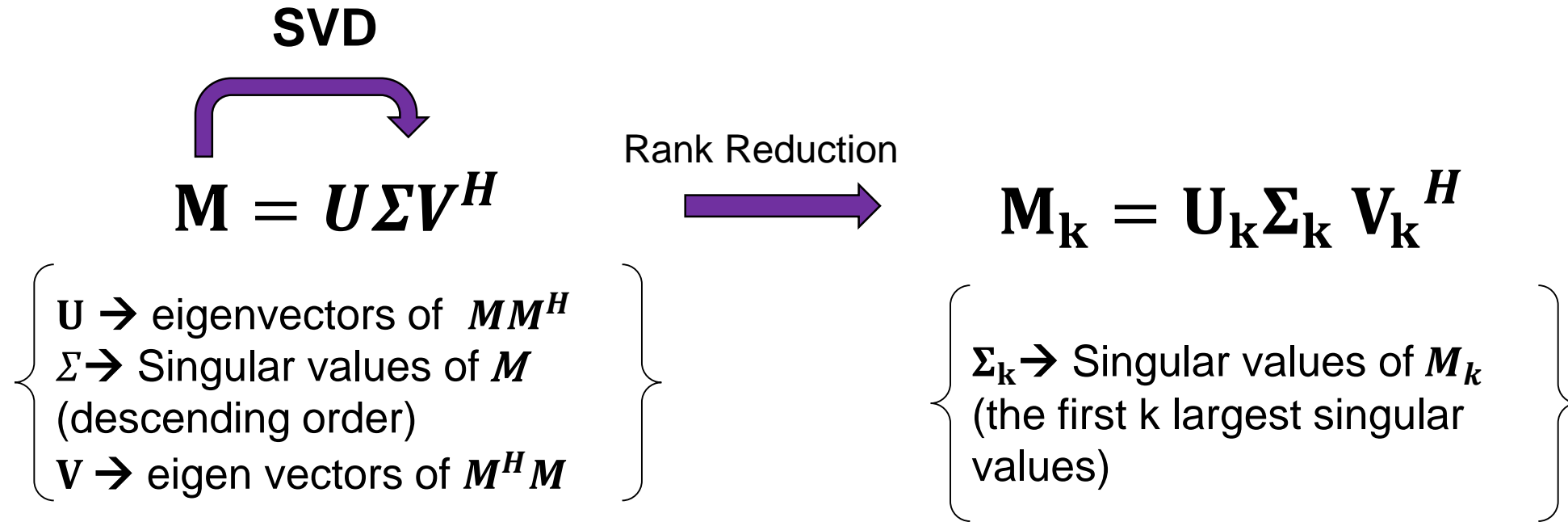


Singular values for noisy data with 51% decimated traces





The rank reduction algorithm

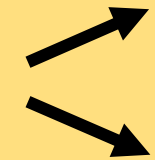


To recover the filtered data \rightarrow
Making average along the anti-diagonals of the rank reduced Hankel matrix



The interpolation algorithm


$$S^{obs} = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \square \begin{pmatrix} S(1,1) & S(1,2) & S(1,3) & S(1,4) \\ S(2,1) & S(2,2) & S(2,3) & S(2,4) \\ S(3,1) & S(3,2) & S(3,3) & S(3,4) \\ S(4,1) & S(4,2) & S(4,3) & S(4,4) \end{pmatrix} = \begin{pmatrix} S(1,1) & S(1,2) & S(1,3) & 0 \\ S(2,1) & 0 & 0 & S(2,4) \\ 0 & 0 & S(3,3) & S(3,4) \\ S(4,1) & S(4,2) & S(4,3) & 0 \end{pmatrix}$$

$T =$


 1 if the point contains an observation
 0 if the point contains an unobserved data

```

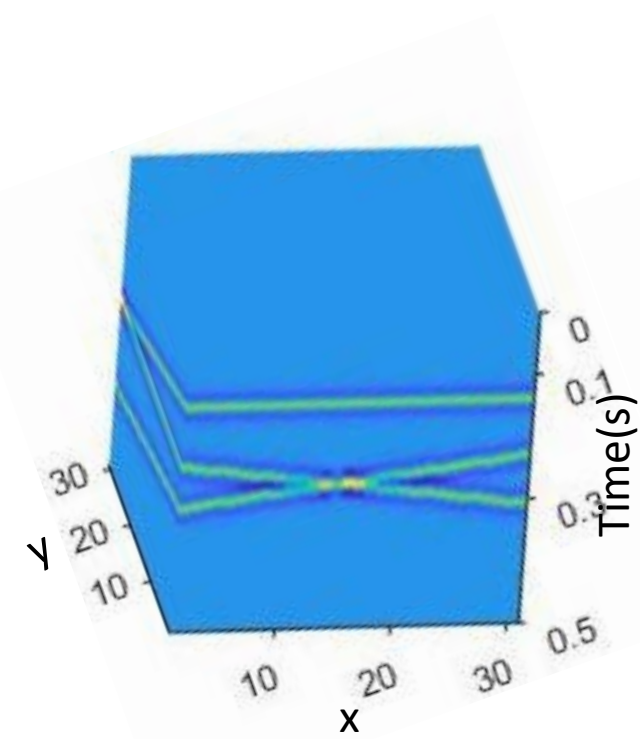
for p=1:Niter
  for f=f1:fN
     $S^p = S^{obs} + (I - T) \square \text{MSSA}(S^{p-1})$ 
  end
end
  
```

The algorithm stops: 

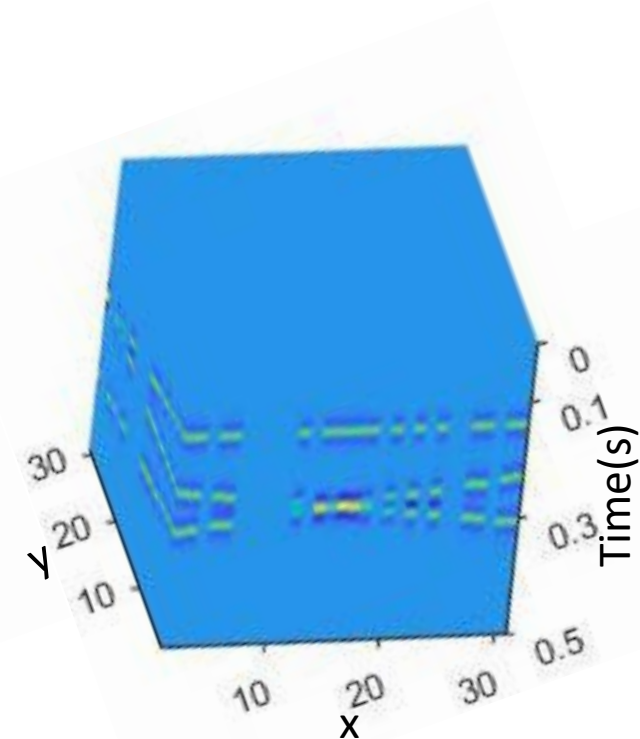
 1. Maximum number of iterations is reached
 2. $\|S^p - S^{p-1}\|_F^2 \leq \varepsilon$



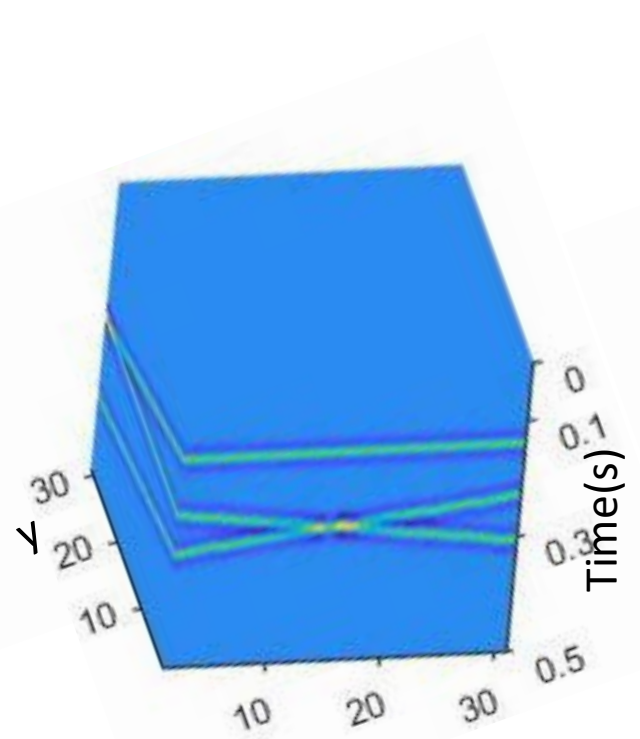
EXAMPLES



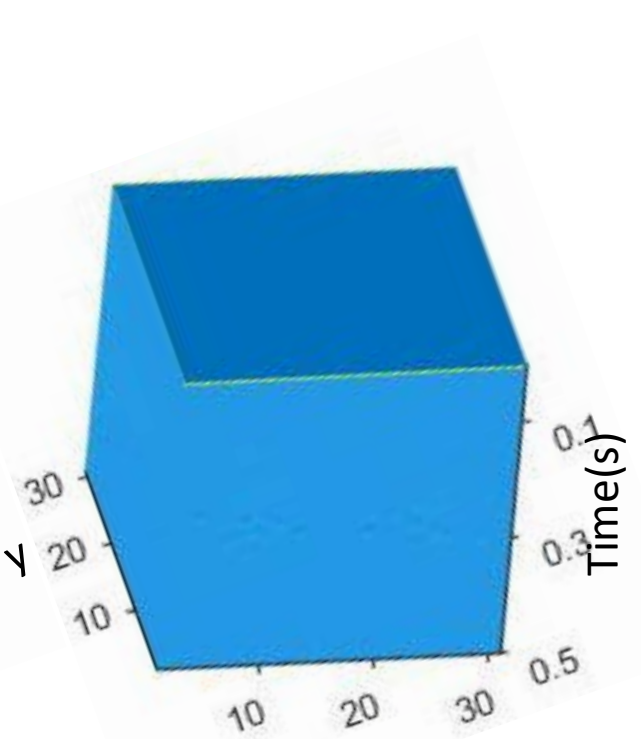
Initial data



Input data with 50% randomly decimated traces



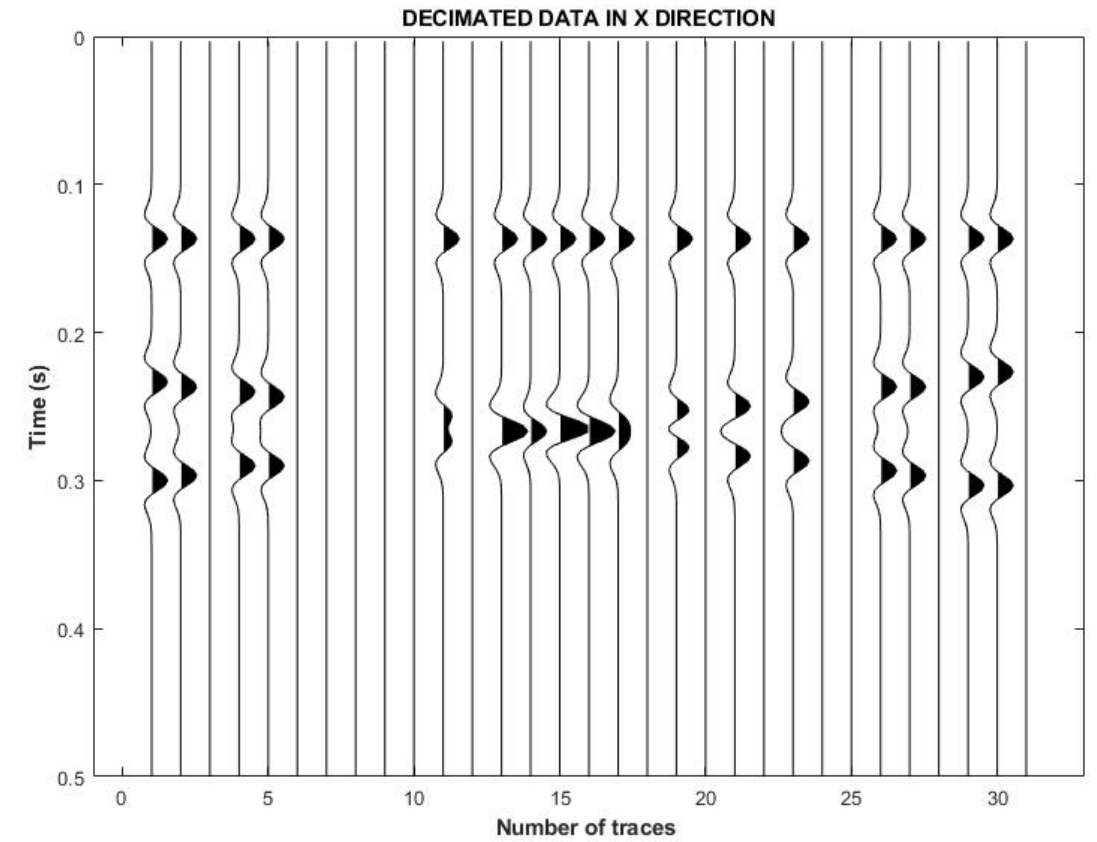
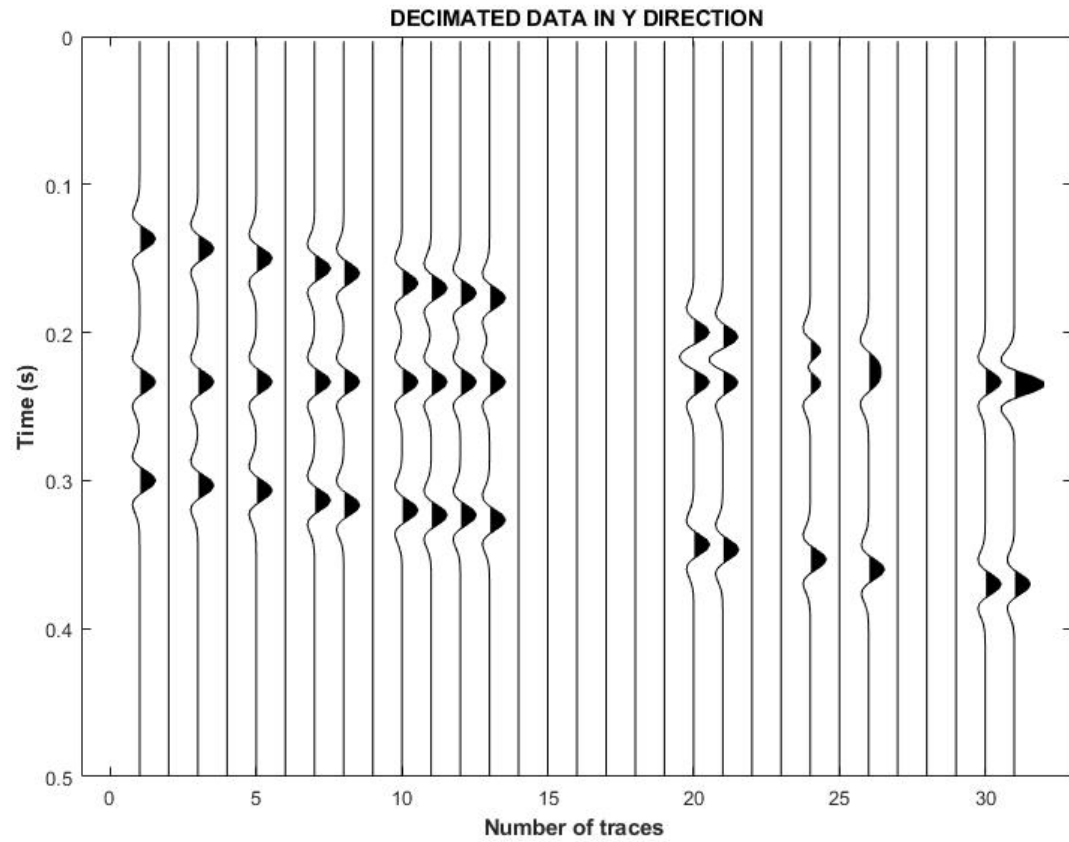
Interpolated data with MSSA



Difference with the initial data

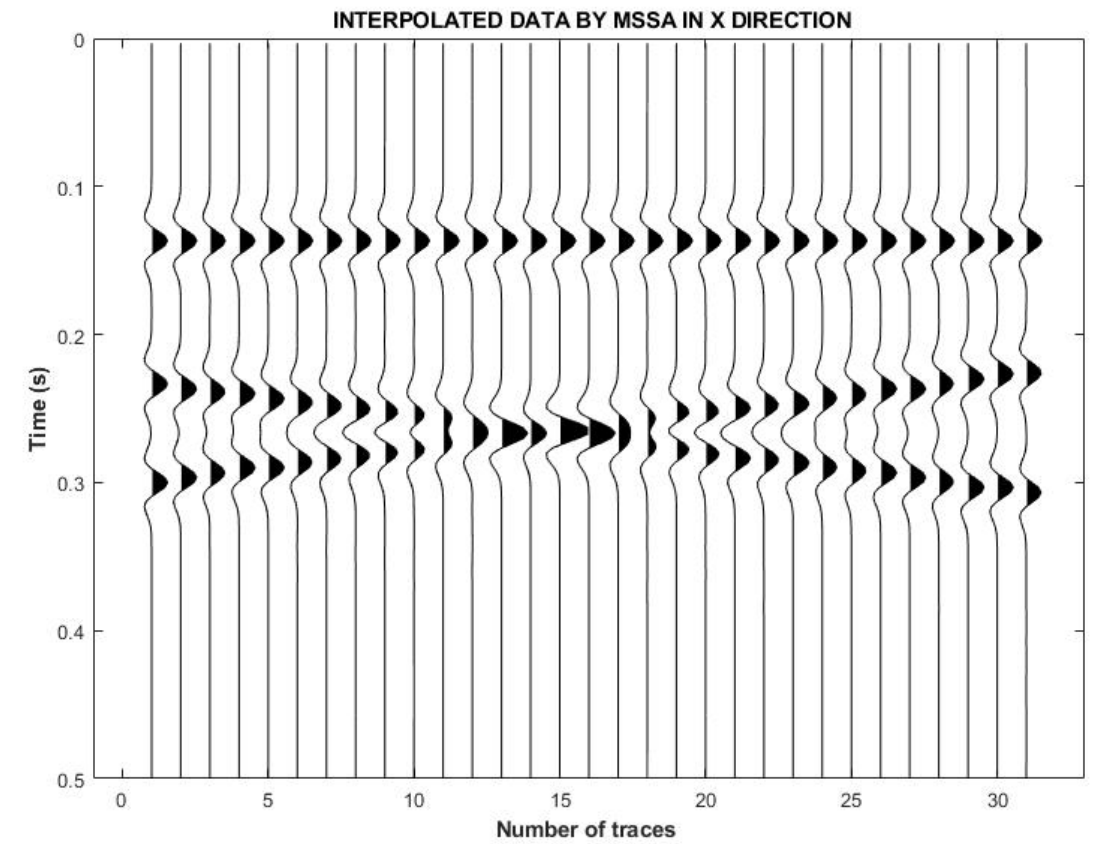
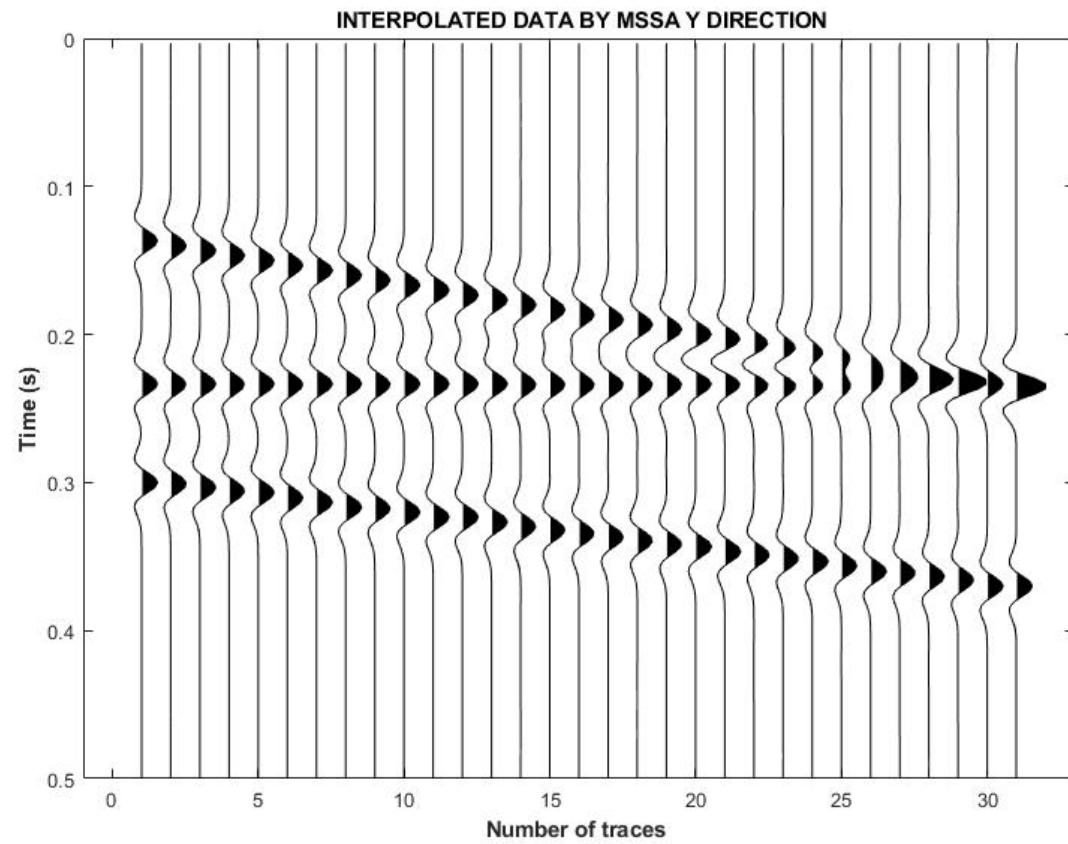


INPUT DATA



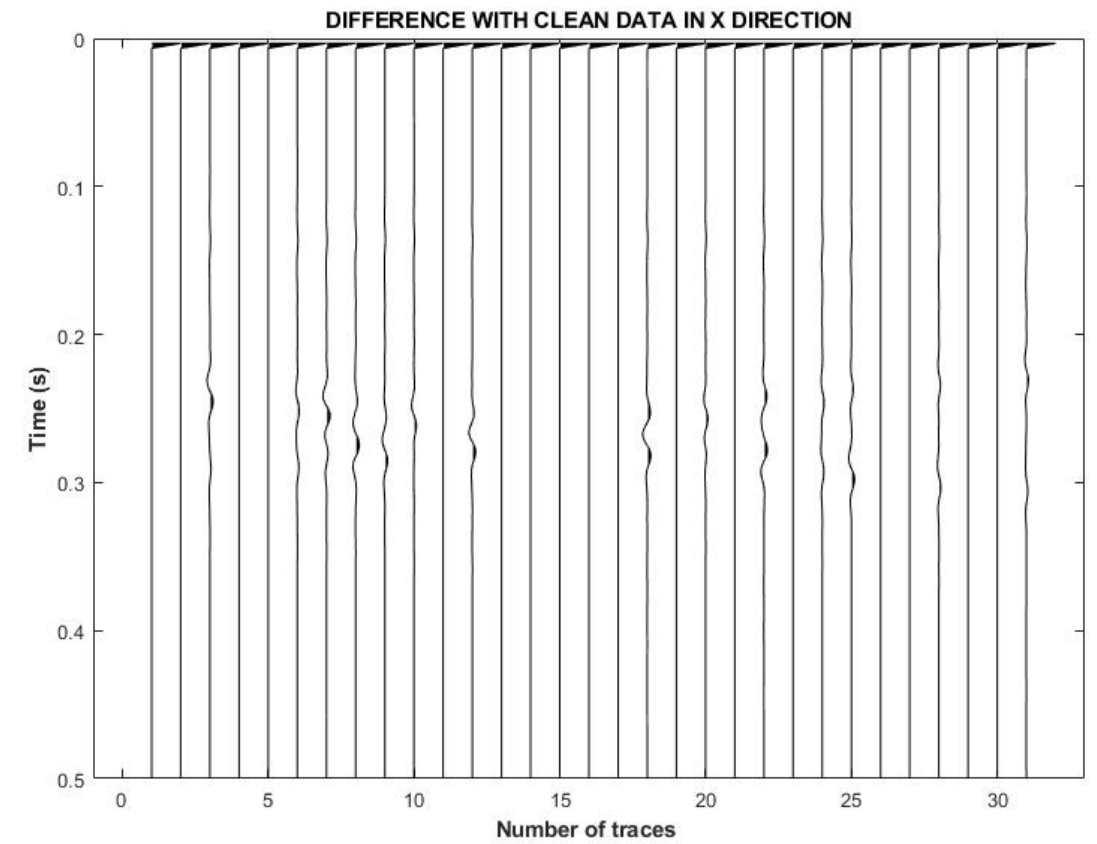
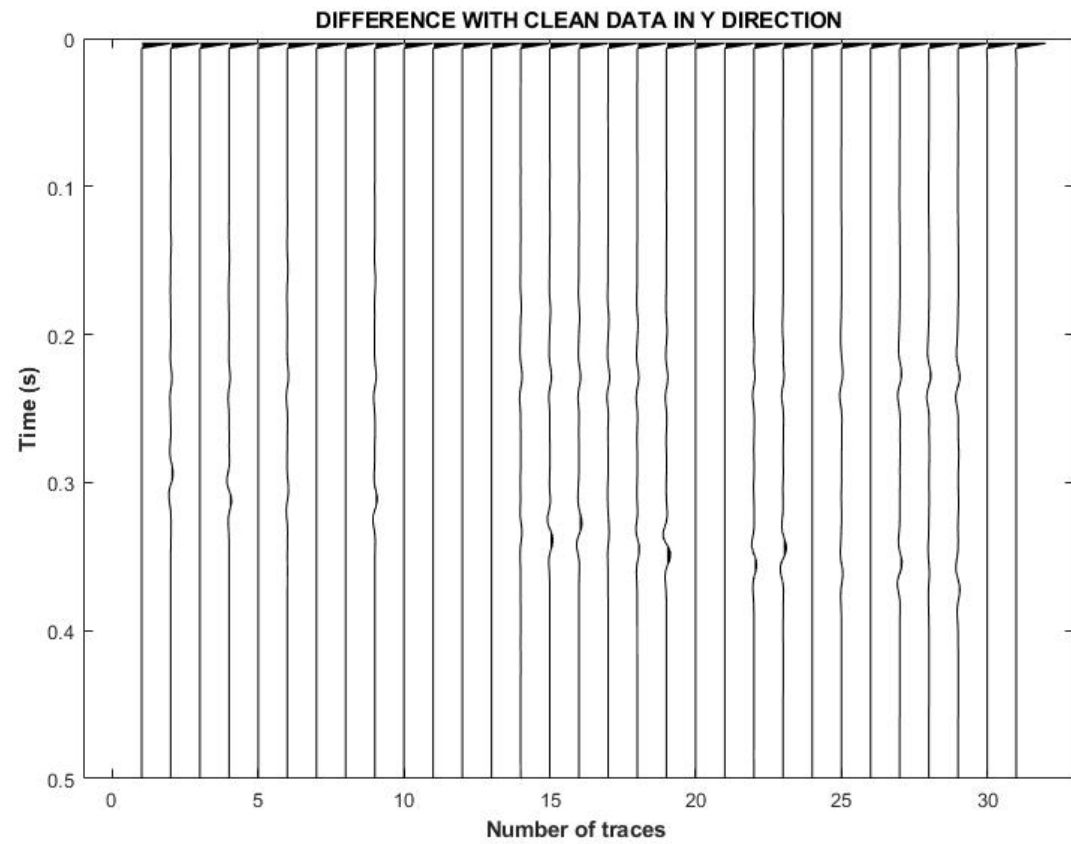


INTERPOLATED DATA



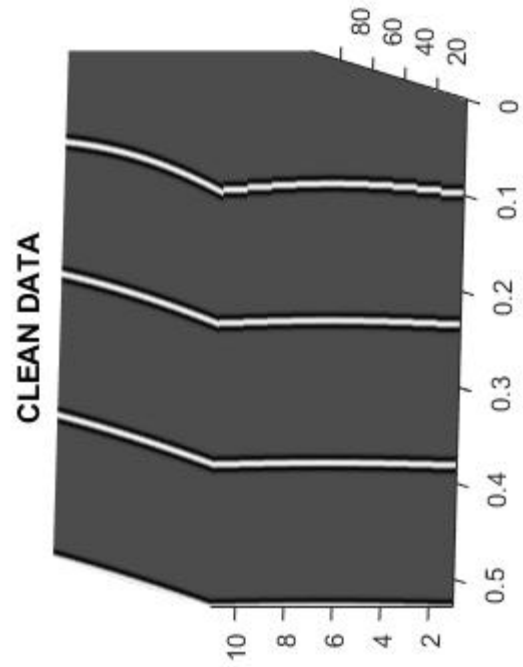


THE DIFFERENCES

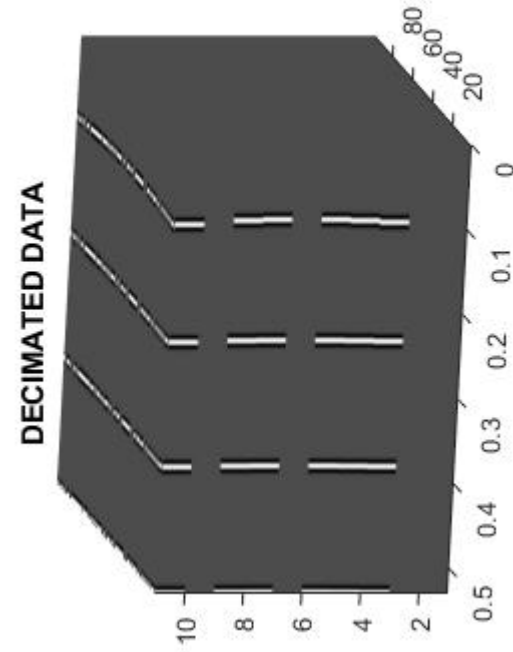




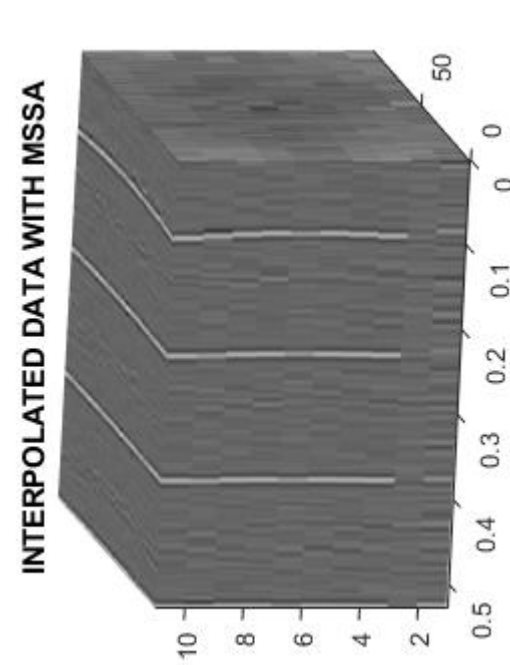
3D prestack data



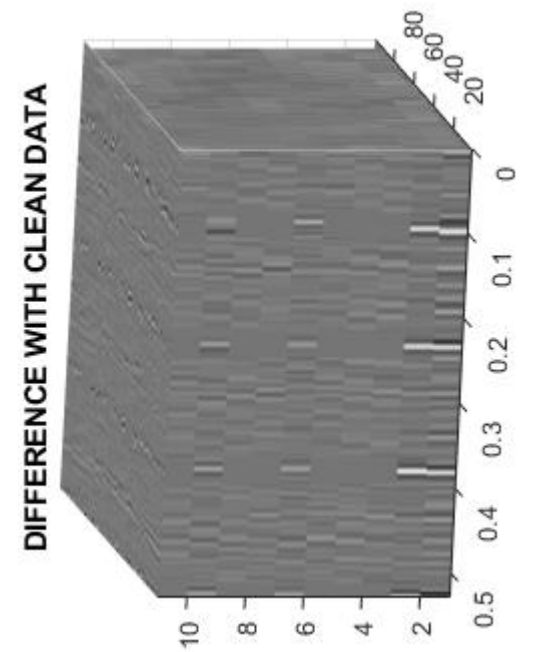
Initial data



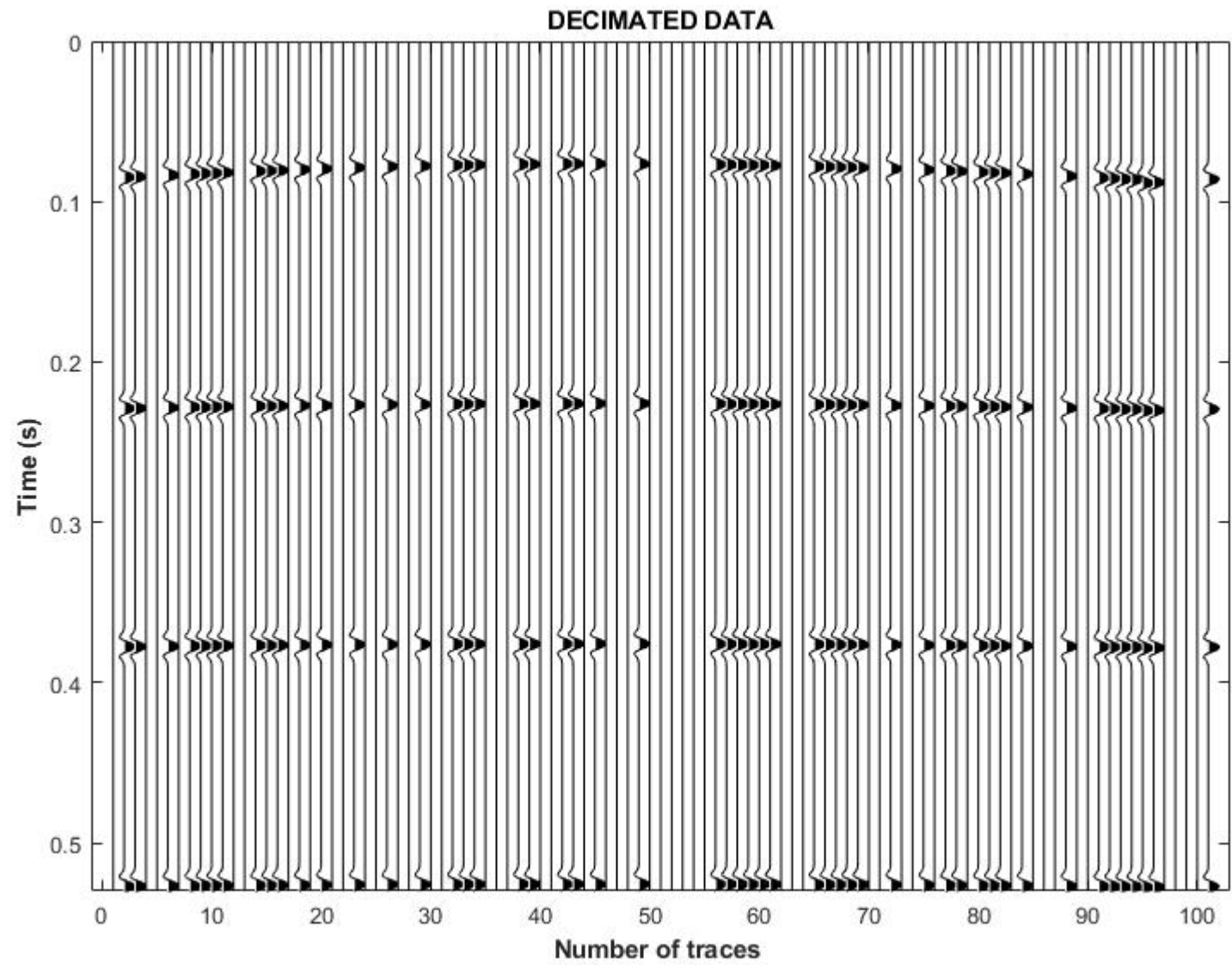
Input data with 50% decimated traces

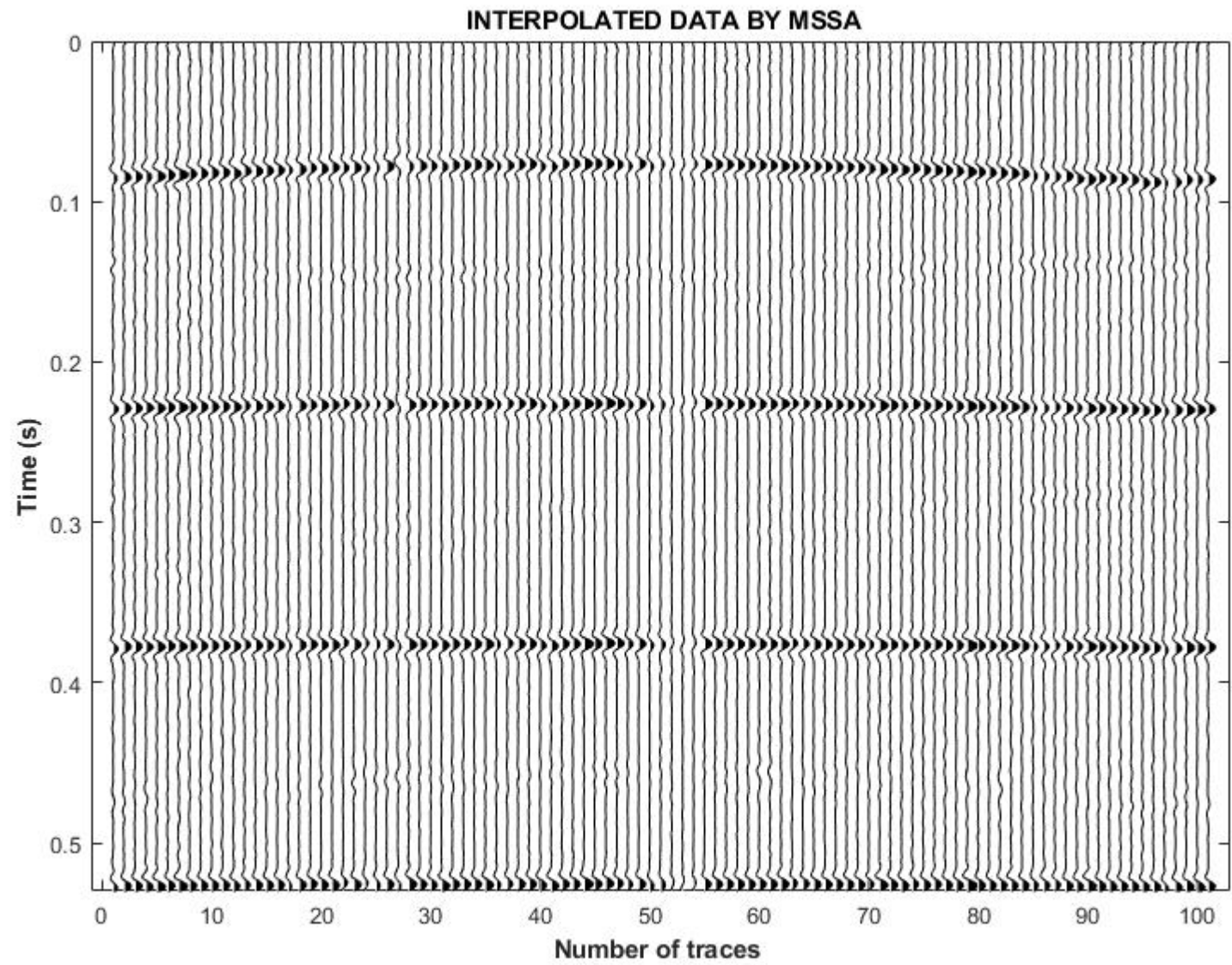


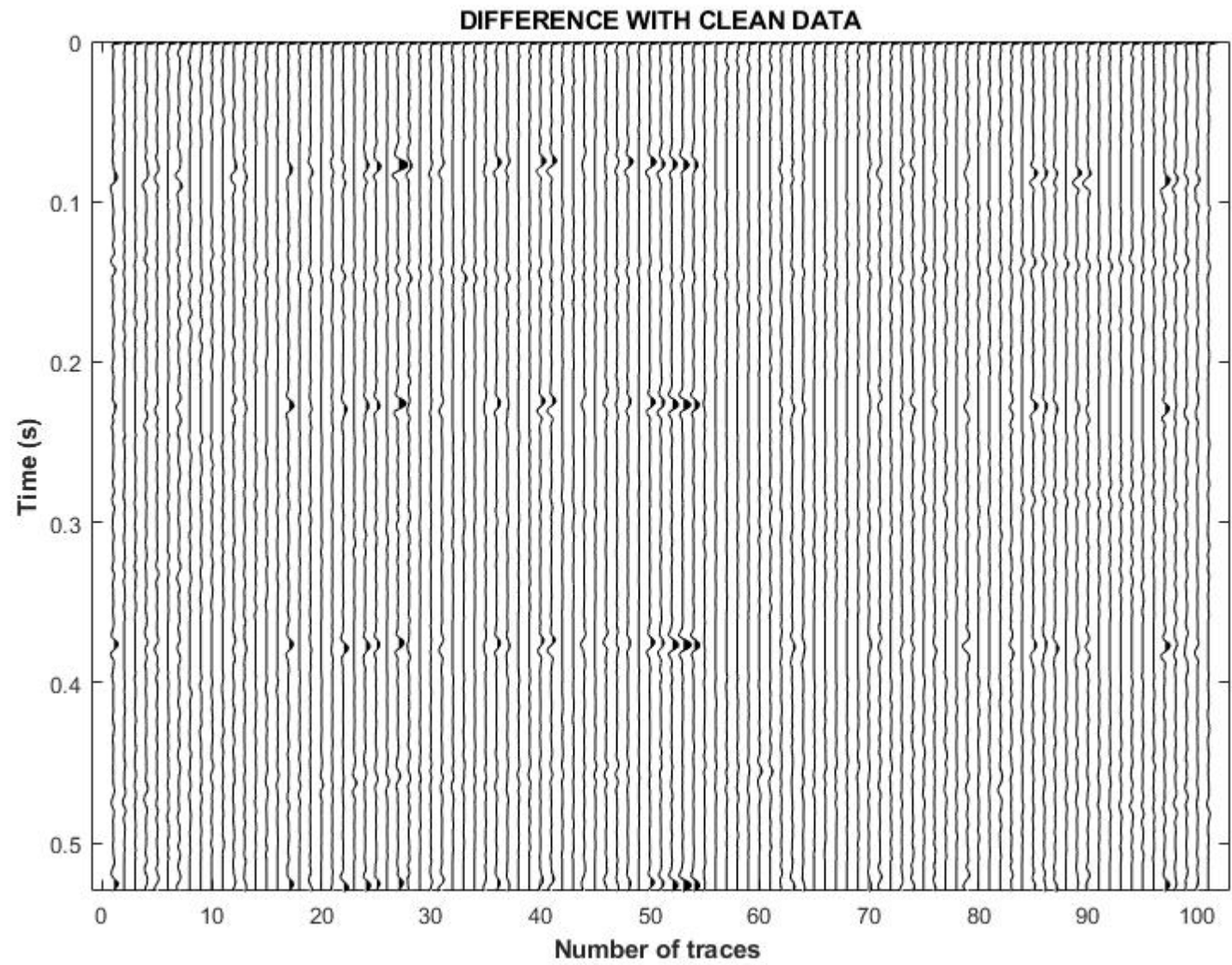
Interpolated traces by MSSA

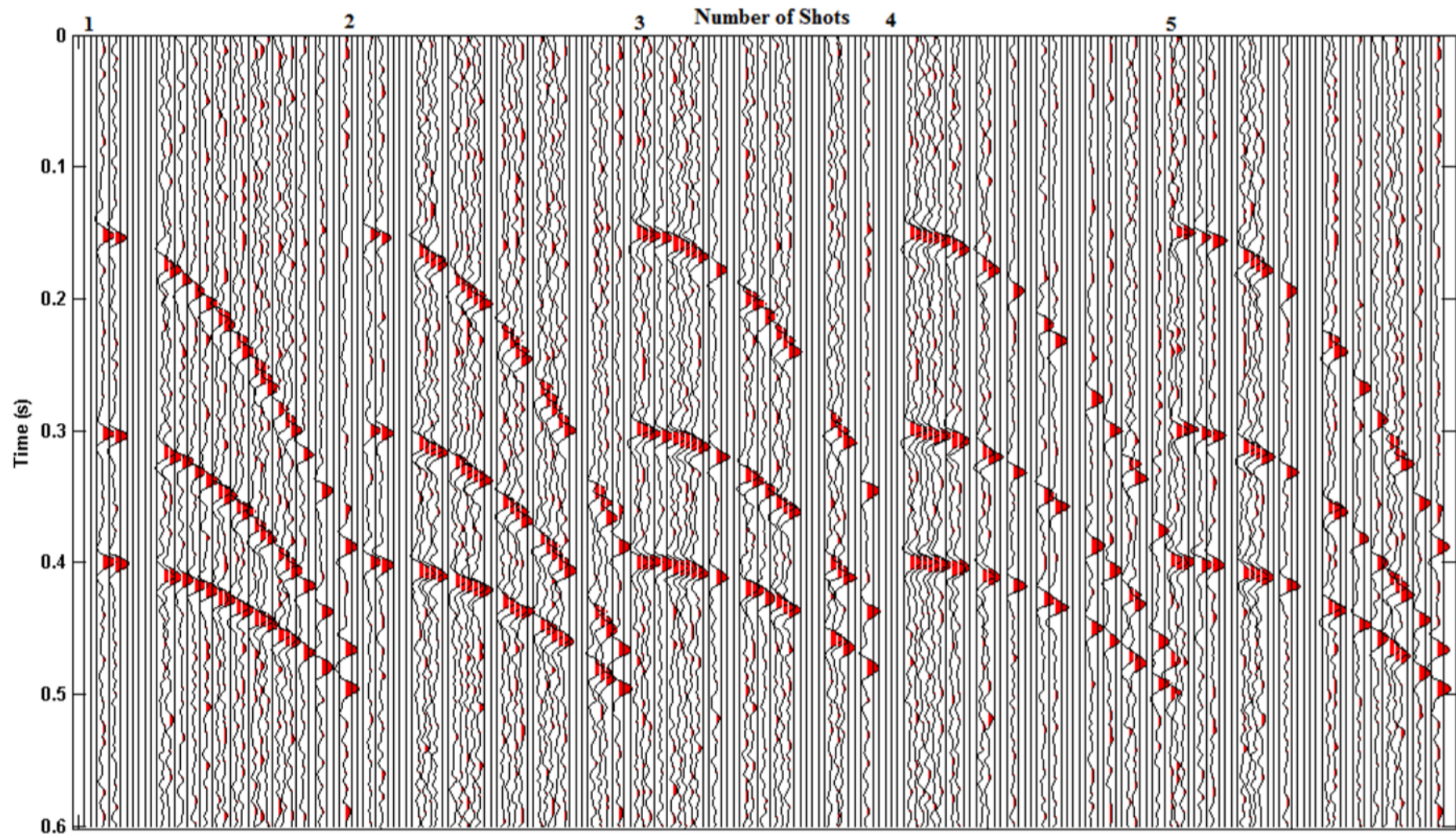


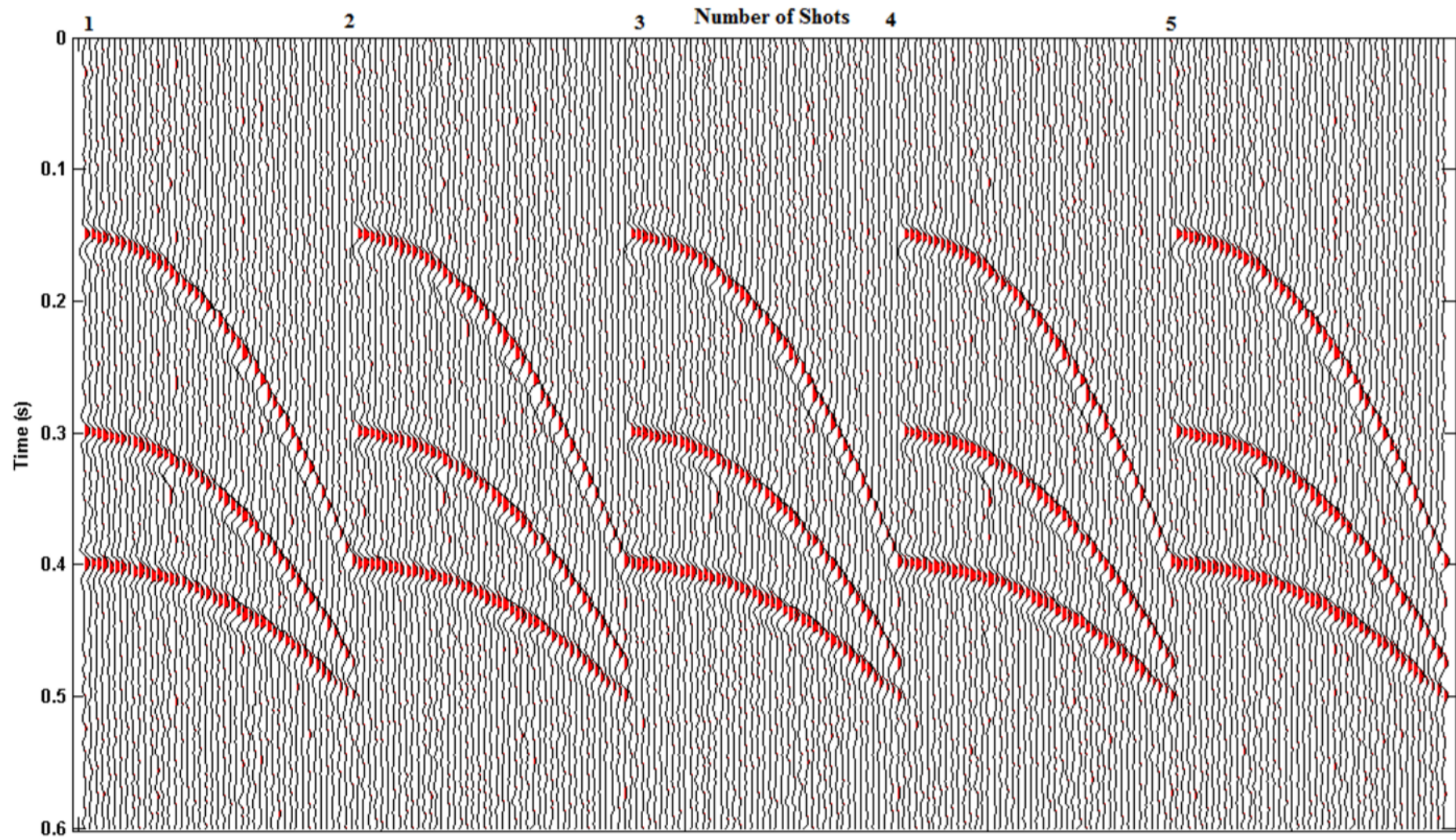
Residuals









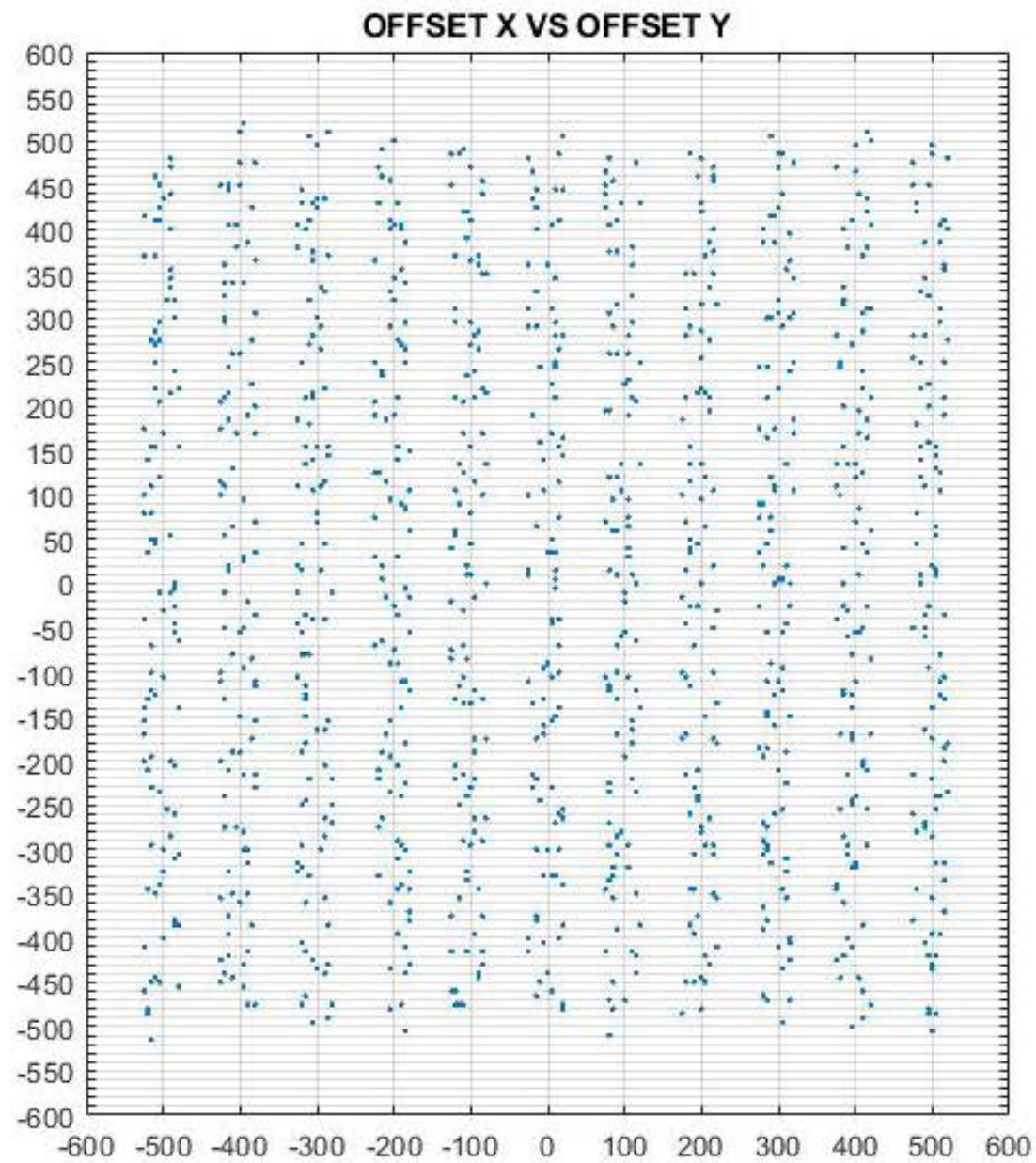
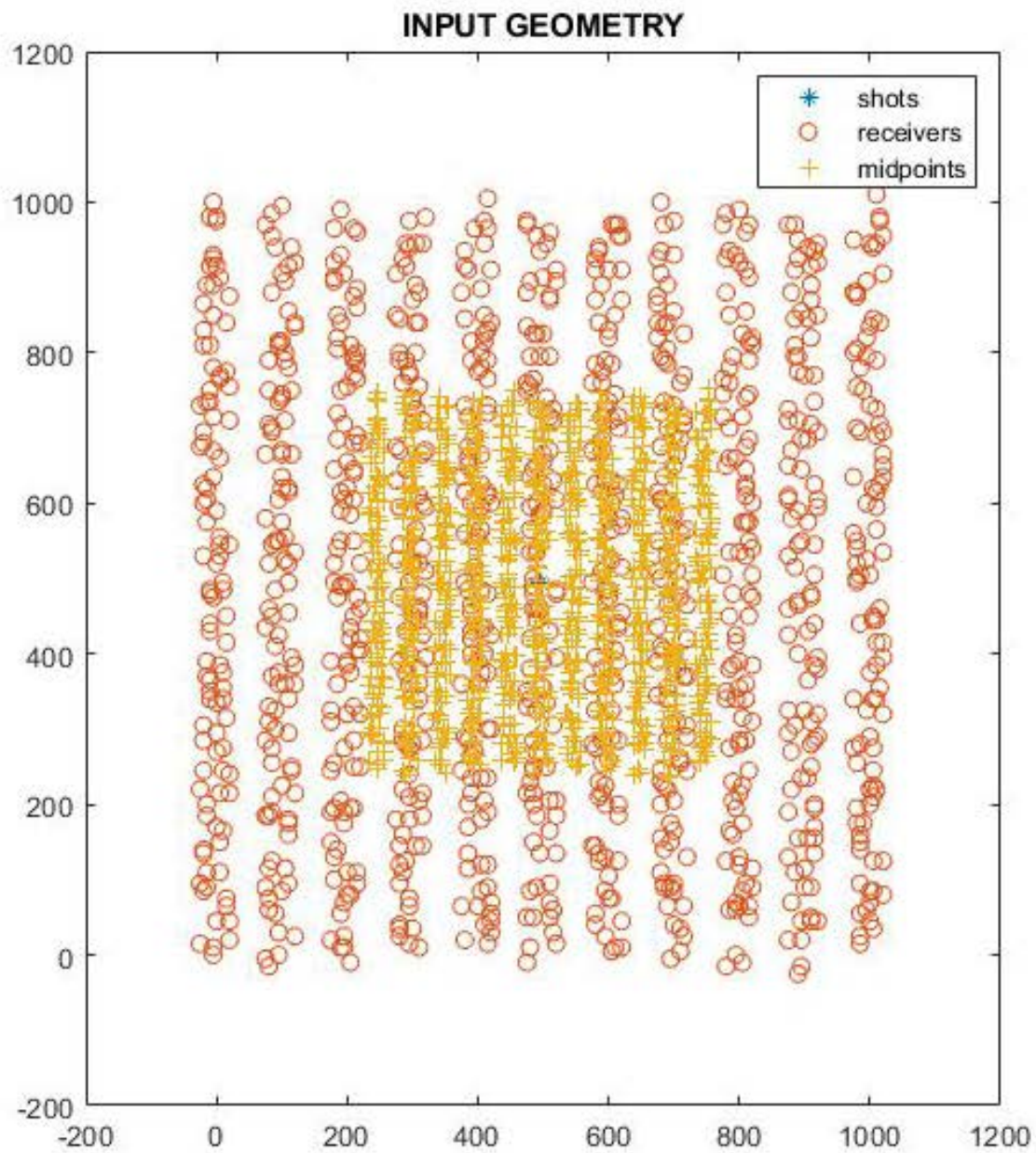


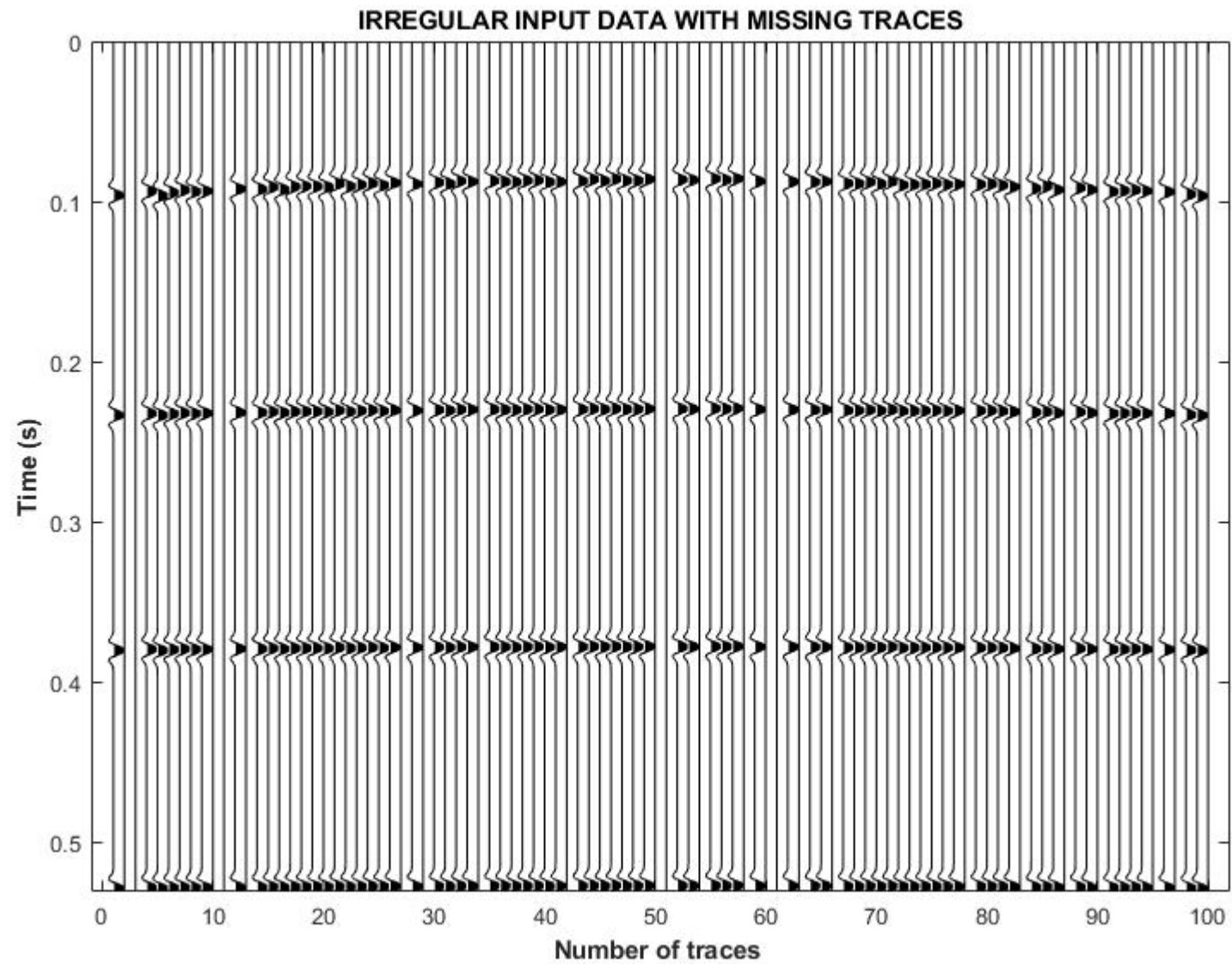


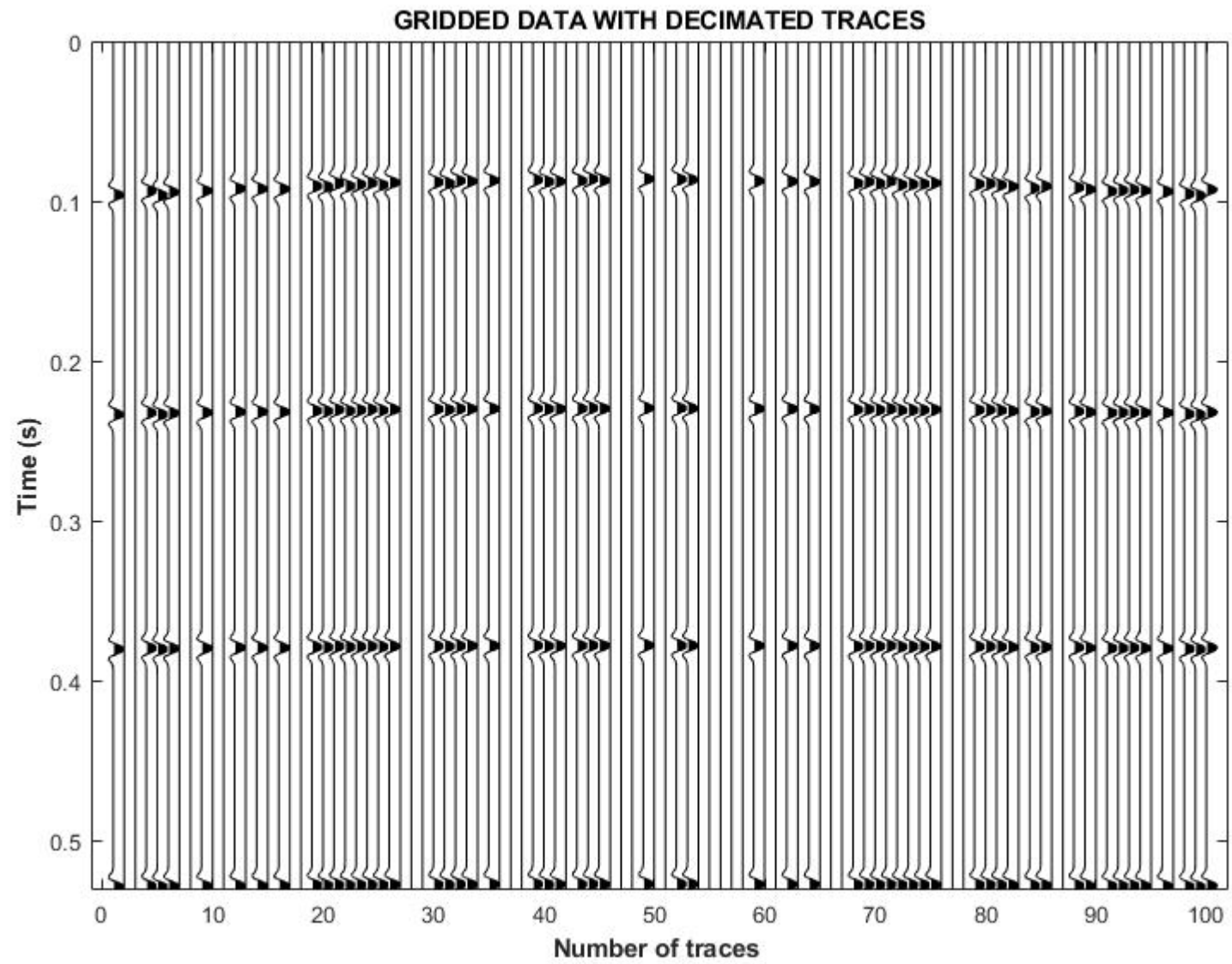
Future work

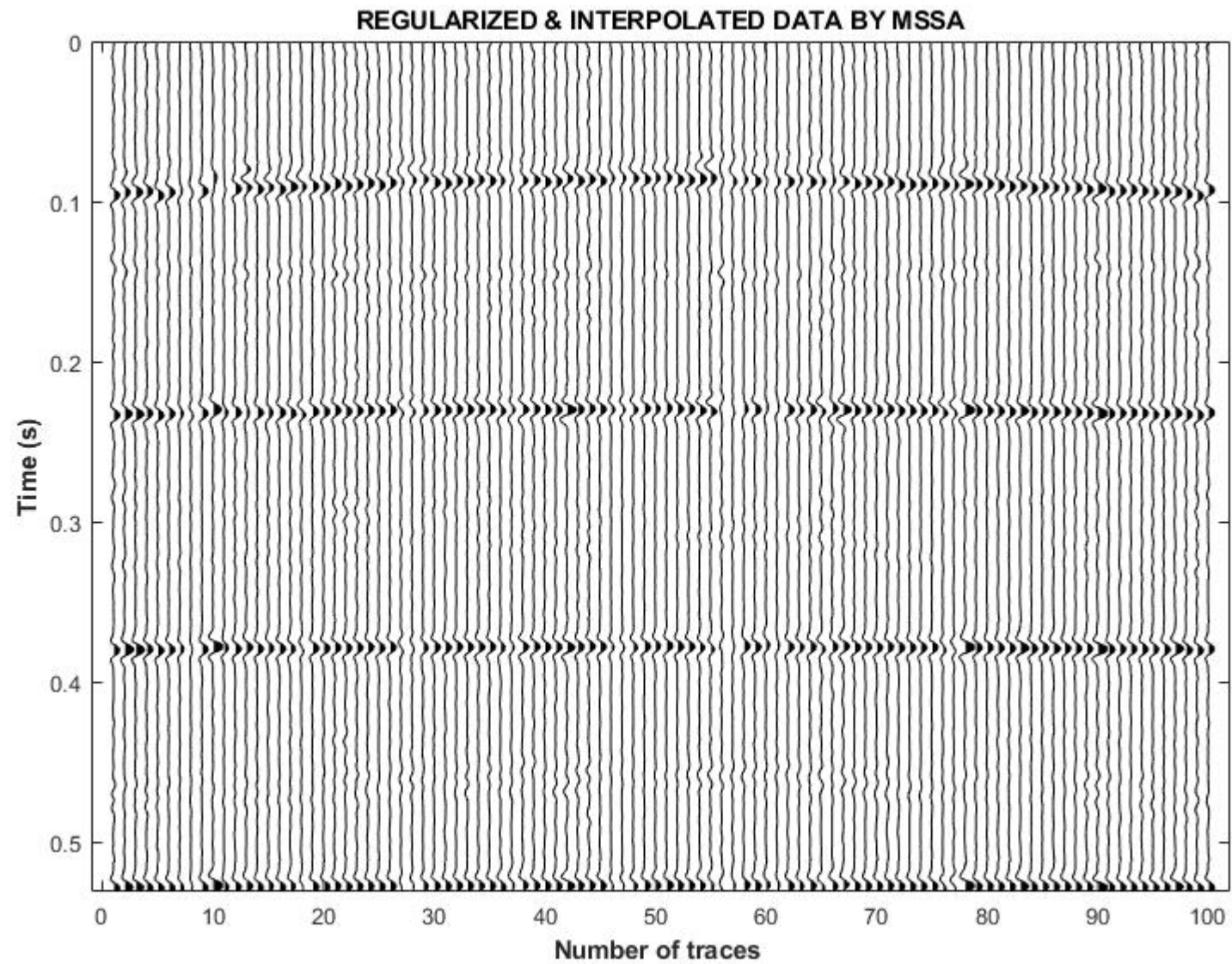


Irregular sampling

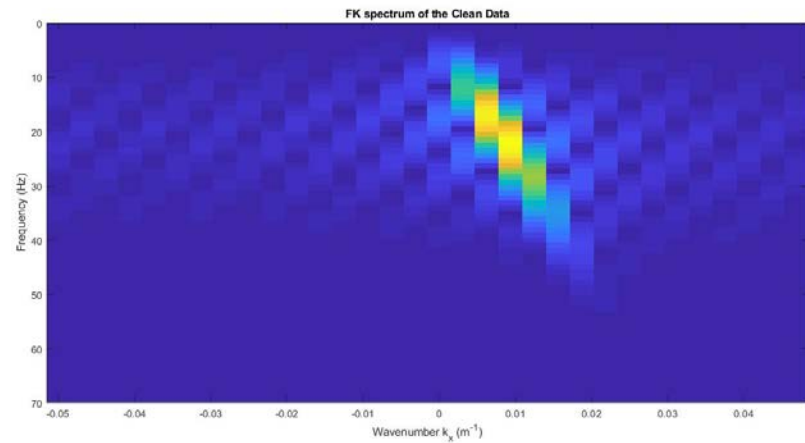
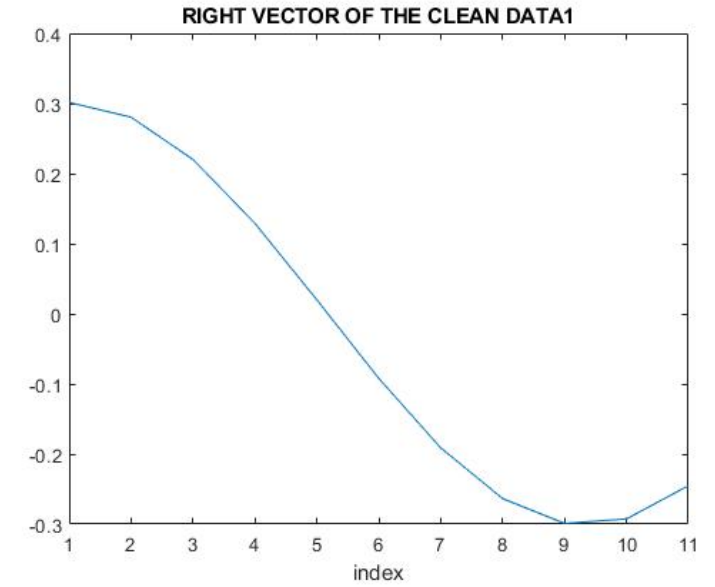
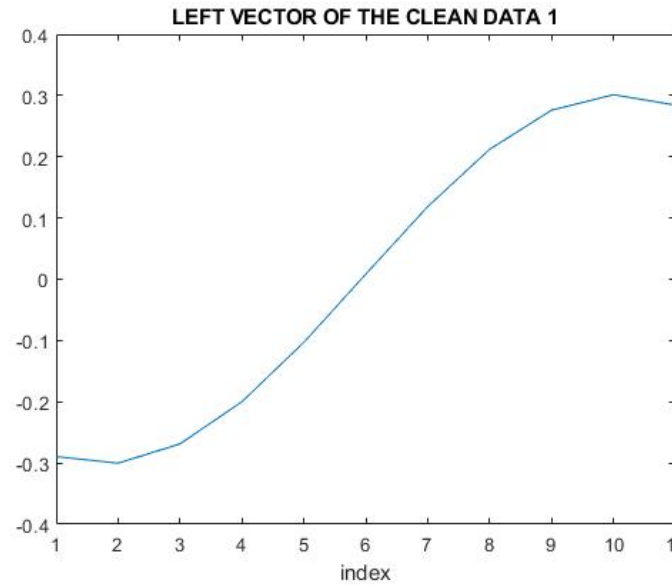
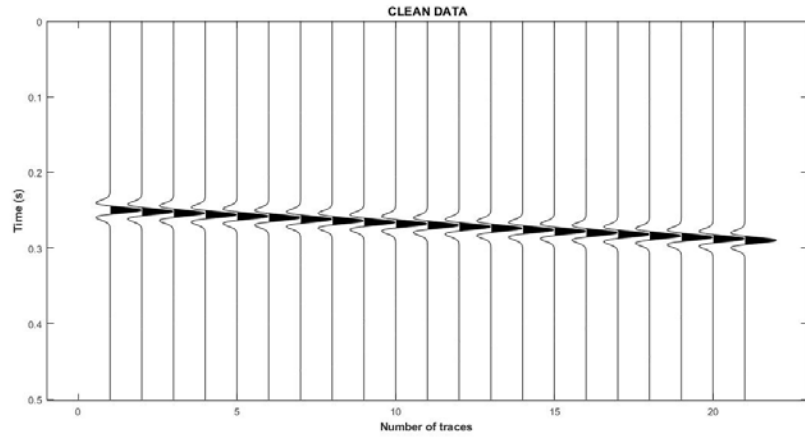




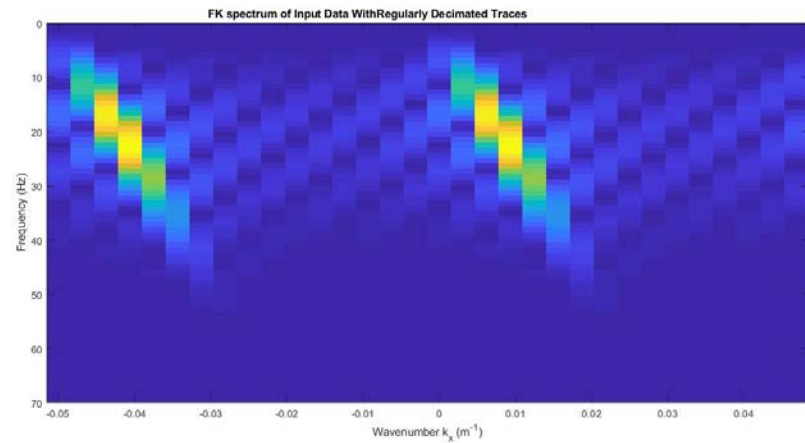
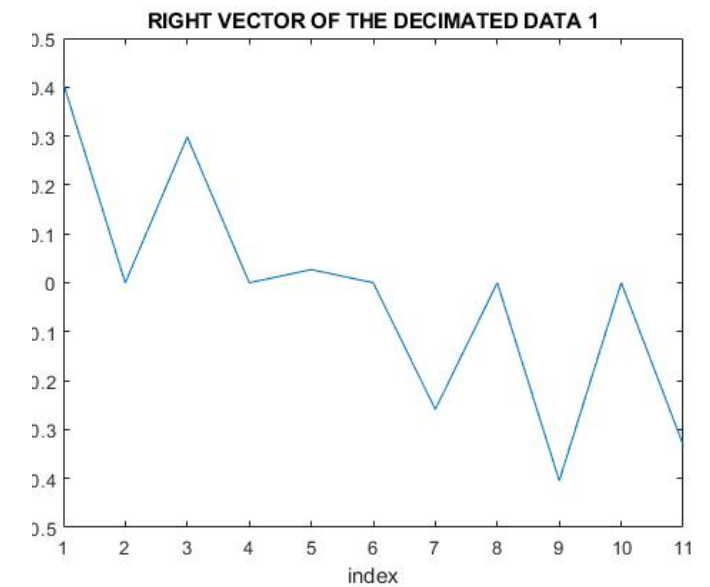
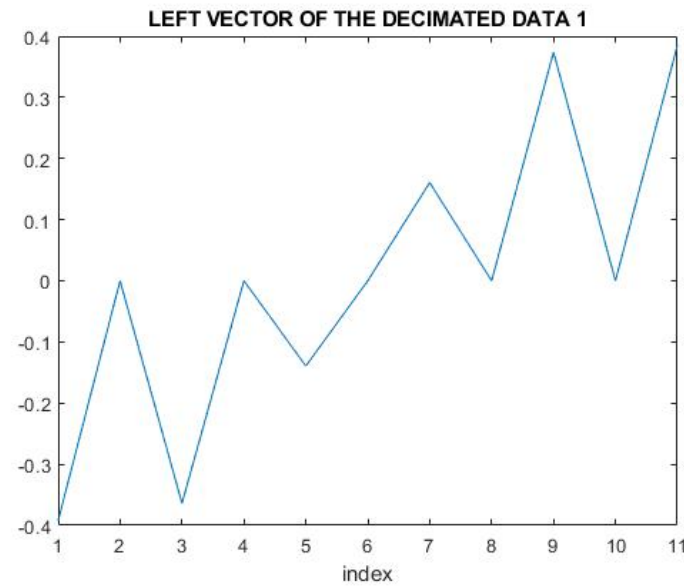
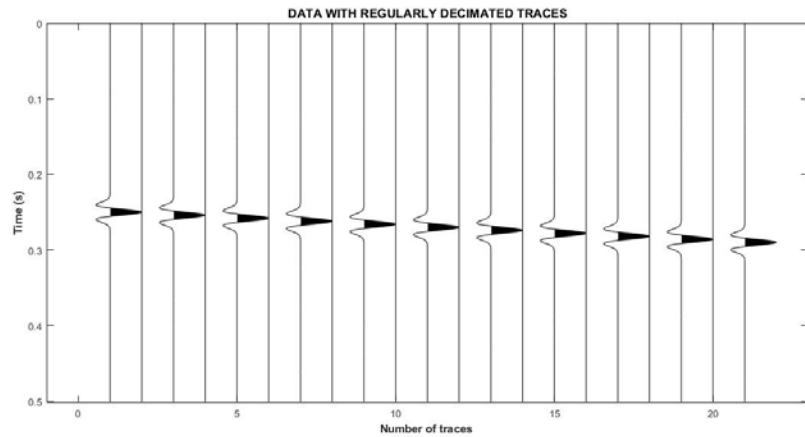




Regularly decimated traces

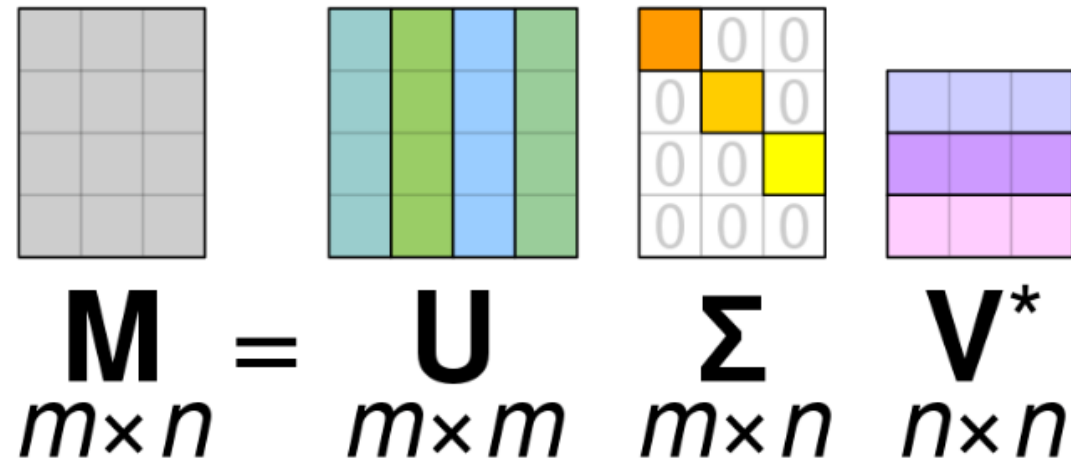
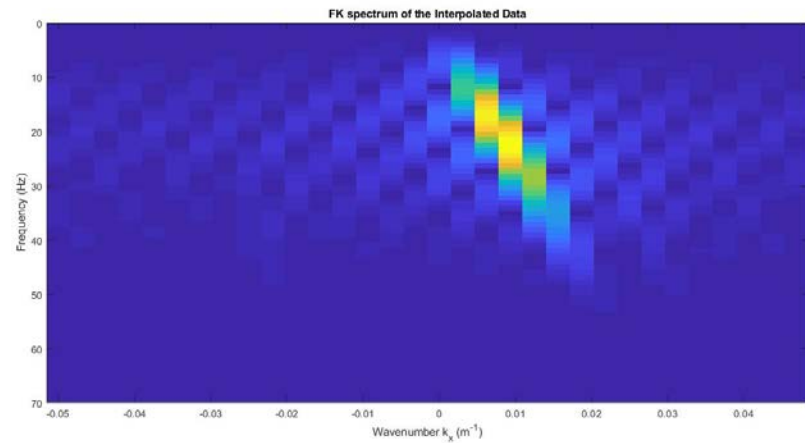
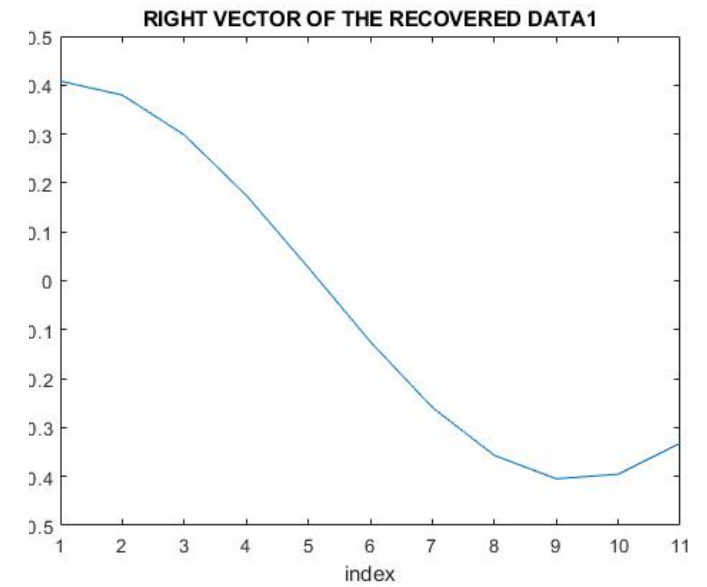
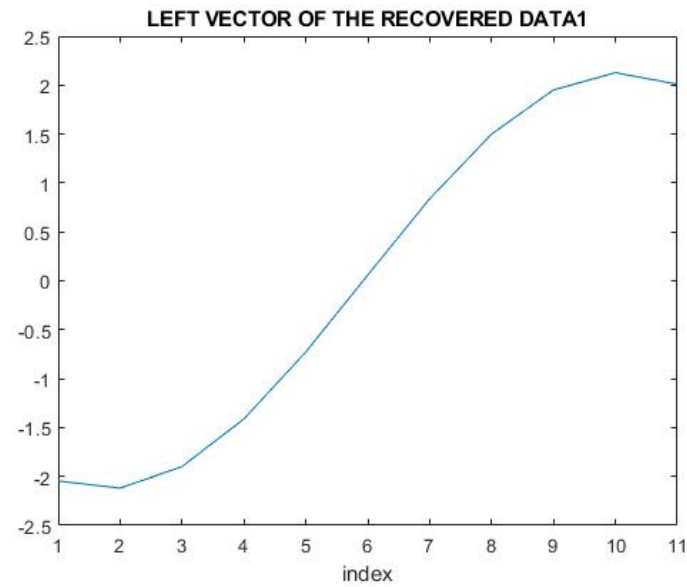
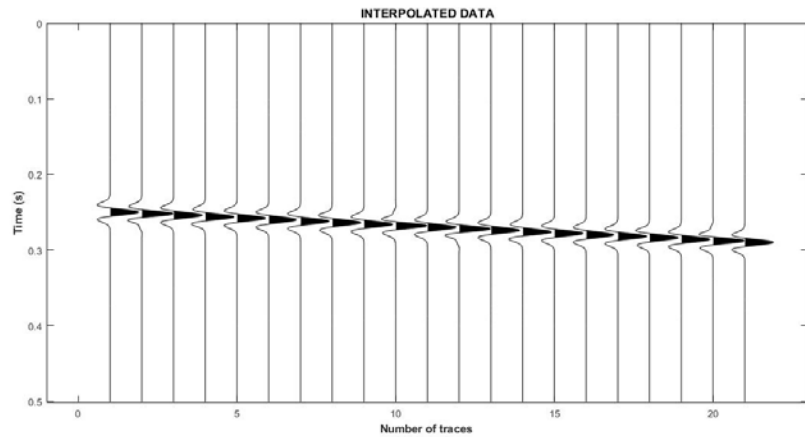


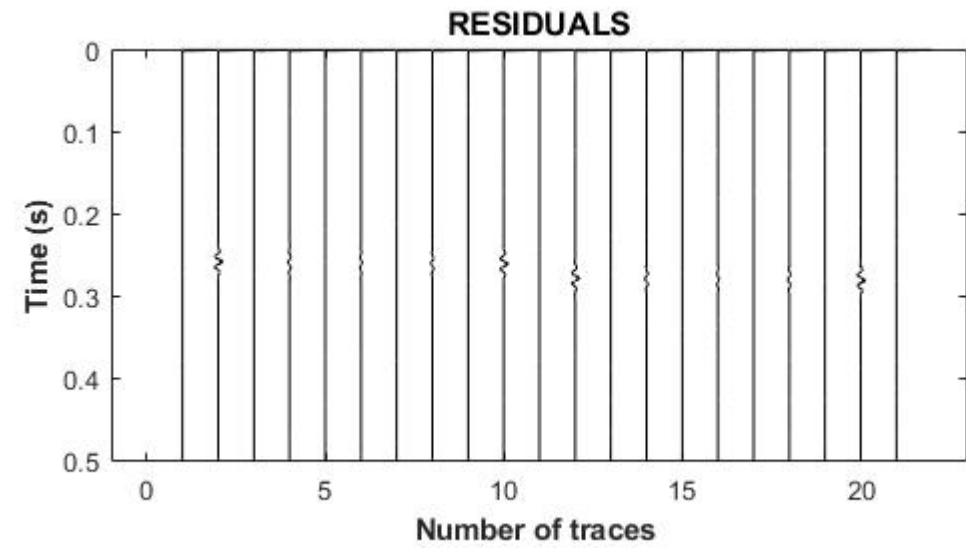
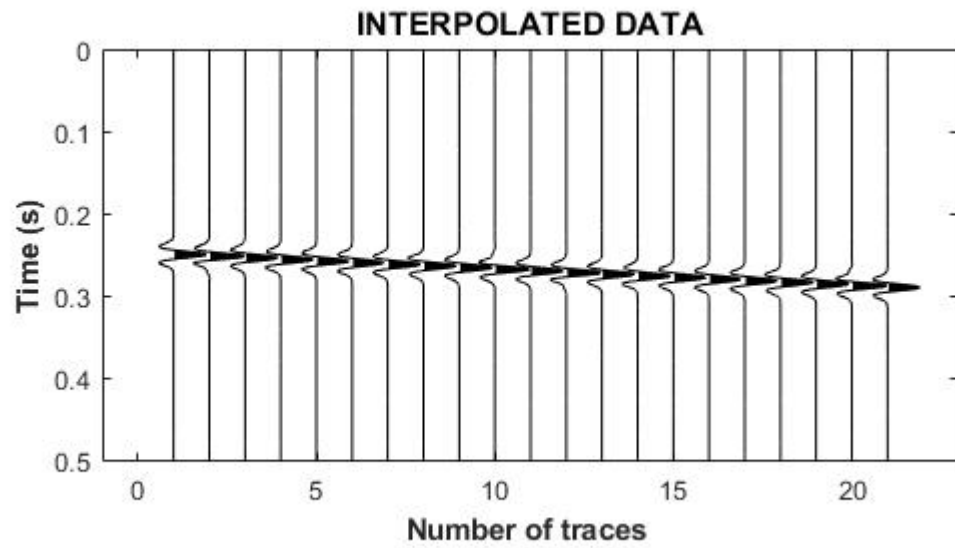
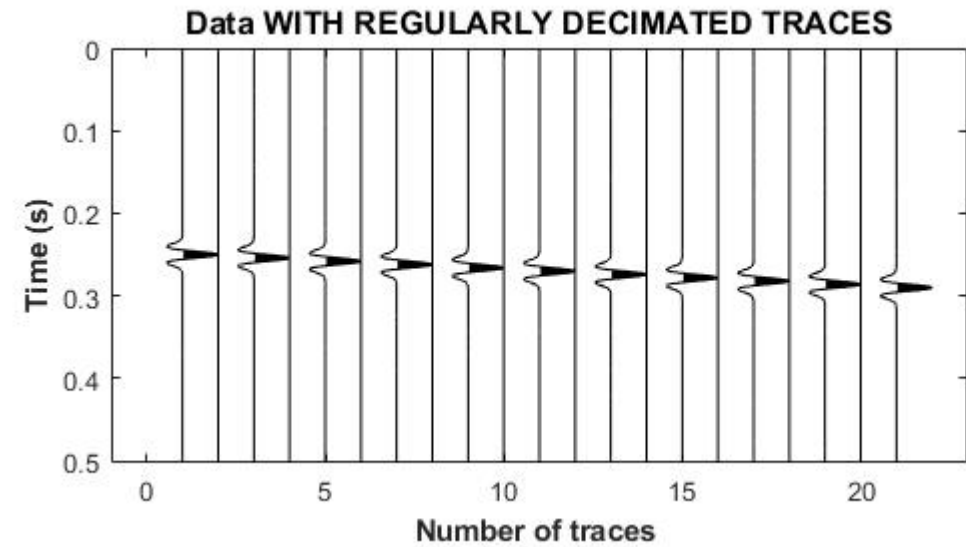
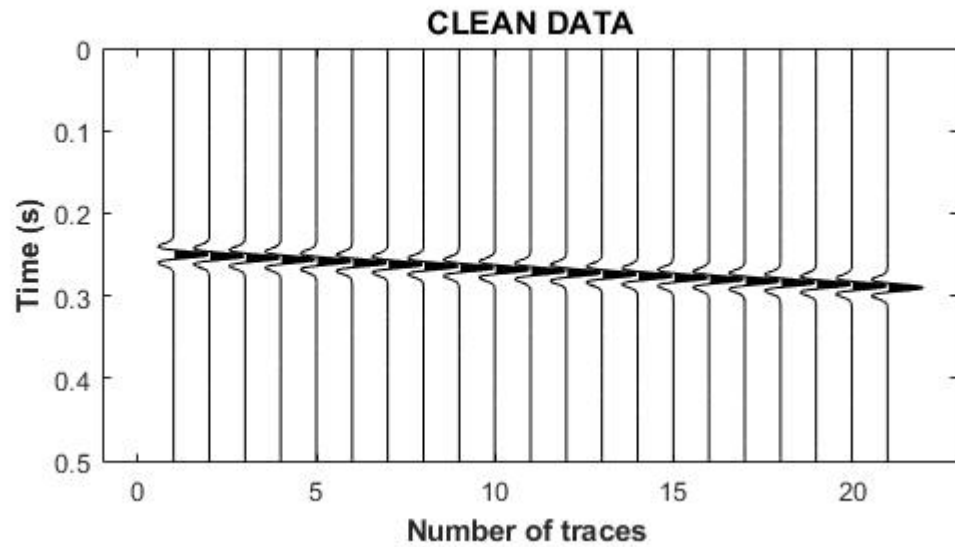
$$\mathbf{M}_{m \times n} = \mathbf{U}_{m \times m} \mathbf{\Sigma}_{m \times n} \mathbf{V}^*_{n \times n}$$



$$\begin{matrix}
 \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} & = &
 \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} &
 \begin{array}{|c|c|c|} \hline \square & 0 & 0 \\ \hline 0 & \square & 0 \\ \hline 0 & 0 & \square \\ \hline 0 & 0 & 0 \\ \hline \end{array} &
 \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array}
 \end{matrix}$$

$$\mathbf{M}_{m \times n} = \mathbf{U}_{m \times m} \mathbf{\Sigma}_{m \times n} \mathbf{V}^*_{n \times n}$$







Conclusions

- Low rank reduction method
- Works in the frequency-space domain
- Forms spatial data into a block of Hankel matrices
- k linear events rank the Hankel matrix of the data k
- Missing traces and additive random noise increase the rank of the Hankel matrix
- Interpolates plane waves, however for the curvature
it needs to set small windows to assume the data linear or
NMO correction before the interpolation to minimize the effect of
curvature
- For irregular data it can work with coarse binning leads to jittering
- Doesn't work for regularly decimated data it needs dealiasing eigen-decomposition of the Hankel matrix



Thank you!