Automatic Statics Correction with Low-Rank Approximation

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Outline

• Introduction
• Rank-based processing
• Low-rank approximation for statics correction
• Numerical examples
• Conclusions
Introduction
Near-surface

- Loose material characterized by a low-velocity layer
- 250 to 1000 m/s, heterogeneous, rapidly changing and season dependent

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Statics (time-shifts)

Statics

(i) Long wavelength statics generated by the lateral variations in the weathering layer

(ii) Short wavelength statics (residual statics)
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Statics correction methods

- Model-based methods:
  - Uphole surveys
Statics correction methods

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  - Refraction traveltime tomography

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✓ Successful Solutions for statics-corrections
  ▸ Cost and time consuming
Statics correction methods

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▷ Cost and time consuming
▷ Unsatisfactory results when violating assumptions
Residual statics

- Errors in estimated models
- Long wavelength methods do not account for:
  - Rapid changes in elevation
  - Base of weathering
  - Weathering velocity
Residual statics correction methods

- Data-driven methods:
  - Stack power maximization

Residual statics correction methods

- Data-driven methods:
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  - Linear inversion
Residual statics correction methods

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Rank-based processing
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- Eigenimage processing
- Interpolation
- Source-separation
- Denoising
Rank-based processing

For a successful rank-based solution in a transform domain:

1. Low-rank signal structure
Rank-based processing

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For a successful rank-based solution in a transform domain:

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3. Structure promotion
Rank-based processing

source-receiver domain  75% missing sources  midpoint-offset domain
Singular values decay

source-receiver domain

midpoint-offset domain

normalized magnitude

singular values

fully sampled data
randomly subsampled data

normalized magnitude

singular values

fully sampled data
randomly subsampled data
Low-rank approximation for statics correction
Rank-based statics correction
Rank-based statics correction

For a successful rank-based solution:

1. Low-rank signal structure (statics-free data)
Rank-based statics correction

For a successful rank-based solution:

2. Structure destruction (data w/ statics)
Rank-based statics correction

For a successful rank-based solution in the (m-h) domain:

1. Low-rank signal structure (statics-free data)
   - Rapidly decaying singular values
Rank-based statics correction

For a successful rank-based solution in the \((m-h)\) domain:

2. Structure destruction (data w/ statics)
   - Slowly decaying singular values
Singular values decay

8Hz

11Hz

55Hz

(s-r)

(m-h)
Rank-based statics correction

For a successful rank-based solution in the (m-h) domain:

3. Structure promotion
   - **Low-rank approximation**: Approximate data by a small number of singular vectors associated with the relatively few largest singular values
Low-rank approximation for statics correction

Our contribution in this work is twofold. First, we present 1- statics correction 2- subsampled land data with statics
Notation
Low-rank representation
Statics correction
Our proposed method utilizes the fact that static time shifts break the continuity and have similar effect to noise, which increases the rank of seismic data, while data without statics can be represented by a low-rank in a transform domain. For a successful low-rank representation, the transform domain of choice should lead to rapidly decaying singular values when the data is statics-free and slowly decaying singular values when the data is affected by static shifts. We choose the midpoint-offset domain to be our transform domain of choice. To justify our choice, we analyze frequency slices at 10 Hz of seismic data with and without statics in the source-receiver domain (s-r) and in the midpoint-offset domain (m-h) along with their corresponding singular values decay curves, (figure 1). We observe that in the (m-h) domain, the singular values decay rapidly when the data is statics-free, while they decay slowly when the data is affected by static shifts, which is not the case for the data in the (s-r) domain. This allows for a low-rank representation. Low-rank representation indicates that the data can be approximated by a small number of singular vectors associated with relatively few largest singular values.

We apply our proposed method on monochromatic frequency slices rather than time slices to increase the computational efficiency by solving over half of the number of slices. In order to well approximate the midpoint-offset frequency slices by a smaller rank, we propose applying NMO correction on the common midpoints (CMPs) before performing low-rank approximation, (Trickett and Burroughs, 2009). The NMO velocity that is used for the NMO correction does not need to be very accurate as the method is robust to NMO velocity errors. We then preform low-rank approximation.

Given a matrix $X \in \mathbb{C}^{m \times n}$ that represent a midpoint-offset frequency slice, we perform singular value decomposition (SVD):

$$X = USV^H,$$

where ($^H$) denotes the Hermitian transpose, $U \in \mathbb{C}^{m \times k}$, $V \in \mathbb{C}^{n \times k}$ and $S \in \mathbb{R}^{k \times k}$ are the matrices holding the left singular vectors, the right singular vectors and the non-negative real-valued singular values of $X$, respectively. We select a small number of singular vectors corresponding to the few largest singular values and obtain a new estimate of $X$ that is of lower rank. We summarize the algorithm of our proposed method as follows:

Algorithm 1 Automatic statics correction using low-rank approximation.

1. Rank $k$ and data $D(t,r,s)$ //Input,
2. Transform the data to the (m - h) domain to obtain $D(t,h,m)$,
3. Pick NMO velocity and apply NMO correction,
4. Fourier transform the data to the frequency domain ($f$),
5. Solve $\hat{X} = USV^H$ using rank $k$ for each frequency slice,
6. Inverse Fourier transform to the time domain to obtain the estimated data with statics correction applied $\hat{D}(t,h,m)$ //output.

We should note that performing singular value decomposition is expensive for extremely large matrices. However for our problem, the computational costs are low since we do not perform reparative singular value decomposition, which makes the method computationally efficient. Variations of SVD such as randomized SVD and other rank minimization techniques can be used to speedup the algorithm when having to deal with extremely large matrices. In the next sections, we apply our proposed algorithm on synthetic and real data examples.
Numerical examples
Synthetic data
Example (i): statics-free data
Example (i): data w/ statics $\pm 100\text{ms}$
Example (i): m-h domain
Example (i): NMO
Example (i): Statics correction
Example (i): Stack

- w/ stat.
- stat. corr.
- stat. free.
Example (ii): statics-free data
Example (ii): data w/ statics
Example (ii): m-h domain
Example (ii): NMO
Example (ii): Statics correction
Example (ii): NMO
Example (ii): Stack

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Example (iii): data w/ statics
Example (iii): m-h domain
Example (iii): NMO
Example (iii): Statics correction
Example (iii): NMO
Example (iii): Stack

- w/ stat.
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- stat. free.
Numerical examples
Real data
Alaska 2D land line 31-81

src: 55
rec: 96
src interval: 440 ft
rec interval: 110 ft
fold: 12

Not much long wavelength statics
Alaska 2D land line 31-81

Conventional seismic processing workflow:
- Geometric spread correction
- Ground roll attenuation
- Datum statics correction
- NMO Correction
NMO-corrected CMPS
NMO-corrected CMPS

Raw

2 passes Res. Stat.
NMO-corrected CMPS

Raw

2 passes Res. Stat.

proposed method
Stack
Stack W/ res. stat.
Stack W/ proposed method
Stack
Stack w/ residual statics
Stack w/ proposed method
PSTM w/ res. stat.
PSTM w/ prop. meth.
PSTM w/ res. stat.
PSTM w/ prop. meth.
Conclusions

- We proposed a **data-driven, computationally efficient** and **automatic** statics correction w/ **low-rank** approximation.
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- Additional benefits include **NMO-stretch correction** and **noise attenuation**.
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- Other rank minimization techniques can be used to speedup the algorithm when dealing w/ large matrices.
- Real & synthetic data examples show the potential of the method.
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Thank you for your attention!