# Intra-array statics and phase corrections obtained by beamforming in the Short-Time Fourier Transform domain: Application to supergrouping

*Dmitry Neklyudov, Institute of Petroleum Geology and Geophysics SB RAS, Novosibirsk, Russia; Andrey Bakulin, Maxim Dmitriev, Ilya Silvestrov, Geophysics Technology, EXPEC ARC, Saudi Aramco*

**Summary**

We present a method to correct for intra-array statics and phase variations pre-stack trace ensembles intended for local summation. We apply the proposed approach as an additional step before summing traces via supergouping. Corrections are derived from beamforming techniques applied in the short-time Fourier transform (STFT) domain performed independently for each frequency component. Beamforming allows to handle more complex variations of recorded signals than simple relative time shifts from trace to trace. Phase correction weights are calculated using SVD of the data matrix in the STFT domain. The proposed approach is demonstrated on synthetic and complex 3D land data from Saudi Arabia.

**Introduction**

Land seismic data often has poor signal-to-noise ratio mainly due to complex near-surface conditions. During seismic data processing, considerable effort is spent to remove the effects of the near surface on acquired data. Every processing step that relies on pre-stack data is challenging because reflected signals are weak, often irregular, and usually hidden behind strong coherent and random noise. Supergrouping at an early stage has been proposed to facilitate processing (Neklyudov et. al., 2015; Golikov et. al., 2015; Bakulin et. al., 2016). The main idea behind supergrouping is to create an enhanced dataset using summation of ensembles of neighboring traces without changing the original acquisition geometry. Supergrouping uses group forming, but can deal with large source/receiver intervals using simple assumptions, that are proven to work well for field data of different complexity. Supergrouping dramatically improves signal-to-noise ratio and allows significantly more robust estimation of processing parameters (residual statics, surface-consistent deconvolution operators, amplitude scaling factors, velocity picking etc.). Improved processing parameters can be applied either to original or enhanced data, as advocated in the Enhance – Estimate – Image approach. Such a strategy was demonstrated on noisy land seismic data acquired in complex near-surface conditions (Bakulin et al., 2016).

Supergrouping uses stacking apertures dictated by existing 3D acquisition geometries that are much bigger than apertures used in standard field groups and can reach several hundred meters. Individual traces in such a supergrouping ensemble, may be recorded over quite different near-surface conditions. These traces can have different intra-array statics and/or variations in the waveforms. Waveform variations may appear as amplitude scaling or more general phase variations. As a consequence, supergrouped data may suffer from suboptimal stacking in the following ways: 1) higher frequencies of desired signals are suppressed, and 2) valuable information about residual statics, surface-consistent deconvolution operators is smeared within the stacking aperture.

We propose a new approach to compensate for these effects and do better than simple stacking. We suggest an effective automatic procedure that is able to enhance desired signals in the prestack seismic data and preserve their important individual properties for further processing. The proposed approach is based on beamforming performed in the Short-Time Fourier Transform (STFT) domain. Corrections are applied for each frequency independently and therefore can handle more complex variations of recorded signals than simple relative time shifts from trace to trace. Corrections are performed in a "local surface-consistent" manner, meaning that trace time shifts and phase variations are calculated with respect to a given reference trace. In the current implementation, the reference trace is taken to be an actual trace from a shot-receiver location in the middle of each supergroup.

**Method**

Consider an ensemble of $M$ neighboring traces. Irrespective of how the traces have been gathered from the dataset, we will treat the ensemble as a linear array. The signal in each trace is given by

$$\mathrm{y}_{\mathrm{k}}(t) = s(t) * h_k(t) + n_k(t) = x_k(t) + n_k(t) \quad (1)$$

where $k$, $k = 1,...,M$ is a trace index in the ensemble, $s(t)$ denotes the desired seismic response (reflected waves) which is presumed to be common for all traces in a given array, $h_k(t)$ denotes the transfer functions of the media which describe differences in near surface conditions for shot-receiver locations, differences in travel path, etc., * means time convolution and $n_k(t)$ denotes additive noise. Applying a STFT to each trace in (1) gives

$$\mathrm{Y}_{\mathrm{k}}(\omega,\tau) = X_k(\omega,\tau) + N_k(\omega,\tau), \quad (2)$$

where $\omega$ is frequency and $\tau$ denotes "time frame" or time of the center of the time window used in STFT. After the STFT each trace is a complex-valued matrix with one dimension representing the frequency and the other dimension being the time frame axis $\tau$. In addition, we consider each frequency independently. In the discrete form, (2) is rewritten as

$$\mathrm{Y}_{\mathrm{k}}^{j}(l) = X_{k}^{j}(l) + N_{\mathrm{k}}^{j}(l) \quad , \qquad (3)$$

where $j$, $j = 1,...,N_{\omega}$ is frequency index and $l$, $l = 1,...,L$ is time frame index. We assume that the transfer functions $h_k(t)$ are slowly varying in time so the following expression is valid in the STFT domain [for details see Talmon et al. (2009) and Doclo et al. (2009)]:

$$\mathrm{Y}_{\mathrm{k}}^{j}(l) = H_{\mathrm{k}}^{j} \cdot S^{j}(l) + N_{\mathrm{k}}^{j}(l) . \qquad (4)$$

For each frequency $H_k^j$, a filter coefficient for a trace with index k, is independent of the time window positions, i.e. it is the same for the whole trace. Since $H_k^j$ is complex-valued and can be given as $H_{\mathrm{k}}^{j} = A_k^j \exp(i\varphi_k^j)$, we assume in (4) that the desired signal in each channel differs by a phase shift and amplitude scaling. We omit the dependency on the frequency index $j$, keeping in mind that it is done independently for each frequency.

Equation (4) can be stated in the vector form as

$$\vec{\mathrm{Y}}(l) = \vec{H} \cdot S(l) + \vec{N}(l) , \qquad (5)$$

$\vec{Y} = [Y_1(l),...,Y_{M_{TR}}(l)]^T$ $\quad \vec{H} = [H_1,...,H_{M_{TR}}]^T$

$\vec{N} = [N_1(l),...,N_{M_{TR}}(l)]^T$ (H means Hermitian conjugate, T is the transpose with no conjugation).

The beamformed output in our case is

$$\hat{S}(l) = \vec{W}^H \vec{Y}(l) = \vec{W}^H \vec{H} S(l) + \vec{W}^H \vec{N}(l) , \qquad (6)$$

where $\vec{W}$ is a column vector of weights. Vector $\vec{H}$ is unknown. Our aim is to determine the weights $W_k$ in order to neglect the impact of transfer functions coefficients $H_k$, i.e. $\vec{H}^H \cdot \vec{W} \approx 1$. Also it is necessary to reduce the impact of the additive noise term in the output.

Stacking procedure (6) may be reformulated in terms of "data matrix," as a matrix-by-vector product,

$$\hat{S}(l) = \vec{W}^H D . \qquad (7)$$

In our case, data matrix $D_{MxL}$ is a complex-valued matrix consisting of $M$ one-dimensional arrays $\mathrm{Y}_{\mathrm{k}}(l)$ as its rows:

$$D_{MxL} = \vec{H} \cdot S(l) + [N_{kl}] . \qquad (8)$$

Here the desired signal $S(l)$ is considered as a $1 \times L$ vector, $[N_{kl}]$ is additive noise matrix.

Following Peterson and DeGroat (1988) and Barros et al. (2015), it is possible to construct a reliable estimator of the vector $\vec{H}$ via Singular Value Decomposition (SVD) of the data matrix,

$$D = U_{MxM} \Sigma_{MxL} V_{LxL}^{H} . \qquad (9)$$

Note that if data matrix (8) consists of only signal and the signal satisfies the model (5), then the data matrix will be of rank one. The signal may be phase-shifted and scaled because multiplication of each row $S(l)$ by complex scalars $H_k$ does not change the rank. In reality, the data matrix is full rank because of dissimilarities of waveforms and presence of additive noise (i.e. signal model (4) usually is not perfect). There are many publications demonstrating that a signal term of a data matrix may be reliably approximated by its eigenimages (Herman and Mace, 1978; Freire and Ulrych, 1988; Grion and Mazzotti, 1998; Trickett, 2003; Ulrych and Sacchi, 2005). As was proven in the literature, the most informative part of the signal term is provided by the first eigenimage of a data matrix

$$EI_1 = \sigma_1 \vec{U}_1 \vec{V}_1^{H} , \qquad (10)$$

where $\sigma_1$ is a largest singular value, $\vec{U}_1$ and $\vec{V}_1$ are corresponding complex-valued (in our case) left and right singular vectors. First eigenimage is the best (in the sense of Frobenius norm) rank-one approximation of a matrix. We use the first eigenimage (10) as an approximation of the signal term of original data matrix (8),

$$D \approx EI_1 + [N_{kl}] . \qquad (11)$$

It is straightforward from (8), (10), (11) that $\vec{H} = \beta \vec{U}_1$ and $\widehat{S}(l) = \alpha \vec{V}_1^{H}$ ($\alpha$, $\beta$ are scaling factors which will be discussed below). For real seismic data, the estimation of the signal $\widehat{S}(l)$ is usually not satisfactory. We propose to use estimation of $\vec{H}$ only to determine the weights and to apply these weights to the original data (not its filtered version given by eigenimages). It follows that an expression for the weights vector $\vec{W}$, which satisfy the desired condition $\vec{H}^H \cdot \vec{W} = 1$ is

$$\vec{W} = \gamma \vec{U}_1 . \qquad (12)$$

As it was noted by Barros et al. (2015), estimates of $\vec{H}$ and $\widehat{S}(l)$, made using rank-one approximation of the signal term, have an ambiguity up to arbitrary scaling factors $\alpha$ and $\beta$, so that $\alpha \cdot \beta = \sigma_1$, subject to $\sigma_1$ is real-valued. It means that the weights $W_k$ should be properly scaled (factor $\gamma$ in (12)) to preserve the correct scale in the output estimate $\widetilde{S}(l)$. We use the scaling $\gamma = 1 \big/ \sqrt{\vec{U}_1^{H} \Phi_{EE} \vec{U}_1}$, where $\Phi_{EE}$ is a correlation matrix of the first eigenimage.

It follows from the condition $\vec{W}^H \Phi_{EE} \vec{W} = 1$, which demands that the beamforming does not change the power of the desired signal (here we use again the approximation the signal term (10)).

We presume that the weights $W_k$ which have been determined using rank-one approximation of the data matrix may be used for phase corrections of actual data (5). We apply these weights to actual data records to make them phase aligned,

$$\hat{Y}_k(l) = Y_k(l) \cdot W_k . \tag{13}$$

Now, we try to take care of the additive noise component. Stacking of weighted data (13)

$$\widetilde{S}(l) = \sum_k \hat{Y}_k(l) \tag{14}$$

will reduce level of additive noise to some degree. For more effective noise suppression we suggest to average the amplitude spectra of $\hat{Y}_k(l)$ before stacking using (14). We apply a complex-to-complex fast Fourier transform for each corrected record (13)

$$F_k(\eta) \equiv FFT < \hat{Y}_k(l) >= B_k(\eta) \exp(i\theta_k(\eta)) .$$

For each "frequency" $\eta$, an averaged power spectrum is calculated,

$$\overline{B}(\eta) = \frac{1}{M} \sum_{k=1}^{M} B_k(\eta) . \tag{15}$$

The average power spectrum $\overline{B}(\eta)$ is "implanted" in Fourier transformation of the data:

$$\overline{F}_k(\eta) = \overline{B}(\eta) F_k(\eta) / B_k(\eta) . \tag{16}$$

By applying the inverse FFT, one obtains corrected version of the records (13), $\hat{Y}_k^{Corr}(l)$ which are stacked in (14).

The proposed procedure is repeated for each STFT frequency j. Finally, the output signal $s(t)$ in the time-domain is reconstructed using the inverse STFT. Below we present results of beamforming applied during supergrouping of synthetic and real data.

**Synthetic example**

In the first example we use synthetic seismograms calculated for the enlarged 3D SEG/EAGE Overthrust model using 3D land acquisition geometry typical for Saudi Arabia. In this example we demonstrate how the proposed approach works with a single ensemble of traces. Note, that we deal with actual traces collected in an array from different shot-receiver positions in a quite complex model. This fact causes variations in the target arrivals among neighbouring traces. Our purpose here is to obtain best estimate of the original reference trace when all three contaminating factors are present simultaneously: random time shifts mimicking intra-array statics, polarity variations of the traces within a group simulating phase distortions, and additive noise.

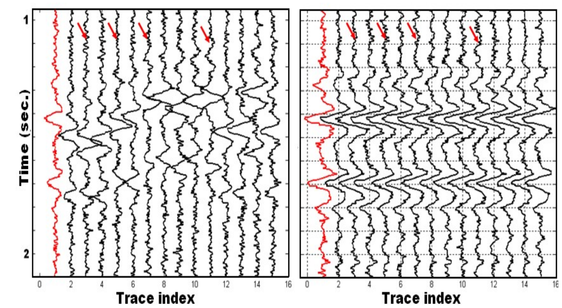


Figure 1: A synthetic example showing (left) input ensemble of 15 traces and (right) phase-corrected traces before stack using beamforming. Some traces have different polarity (marked by red arrows).

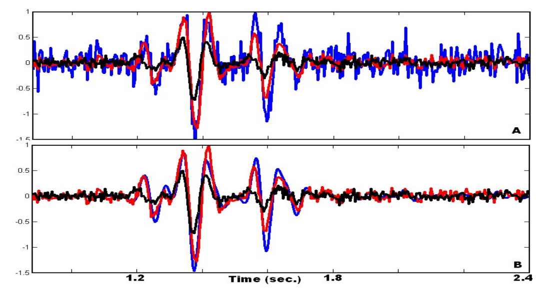


Figure 2: Comparison of the output stacked traces with the noisy reference trace (top) and with the noise-free reference trace (bottom). Blue is the reference trace, black is the output trace obtained using max cross-correlation criteria and red is the output trace obtained using beamforming.

We consider a super group of 15 synthetic traces. The size of the group is 500 by 200 m or 3x5 traces (To construct the group we use three neighbouring common shot gathers in inline direction and five common shot gathers in crossline direction). Random time shifts of up to +/-80 ms are applied. In addition, some traces have changes in polarity. White Gaussian noise is added to the data so that the signal-to-noise ratio (SNR) is equal to -2 dB. Figure 1 (left) shows the input ensemble after introducing all three contaminating factors. The contaminated reference trace is shown in red. The result after beamforming is shown in Figure 1 (right) as an ensemble of corrected traces before summation. One can see that all traces in the ensemble are aligned after applying beamforming corrections. Comparisons of the output stacked traces with the reference traces are presented in Figure 2. We also compare the proposed approach with conventional time-delay estimation which determines relative timeshifts via cross-correlation between traces. We clearly see that red beamformed trace provides excellent approximation to the blue noise-free reference trace (Figure 2, bottom). We also note that beamforming provides much better estimate than simple maximum cross-correlation estimator (red vs. black traces on Figure 2).

**Field data examples**

In the first real data example the proposed approach has been used for a challenging 3D land dataset from Saudi Arabia. The dataset has already been processed for velocity analysis and imaging. As one can see in Figure 3 (top) there are no visible reflections in the original CDP gather. The middle panel shows the same CDP gather after enhancement similar to supergrouping, but in the CDP-offset domain (240 by 100 m) where each trace in the enhanced CDP gather is a stack of approximately 55 neighbouring original traces. Reflections are easily recognizable at near and medium offsets. At far offsets reflections are not visible due to non-optimal stacking. This fact is especially obvious when compared to corrections obtained by beamforming approach (Figure 3, bottom). The length of the time window used for STFT is 100 ms, whereas time frame sampling is 20 ms. Reflections are visible over the entire offset range. Sharp time shifts are distinguishable. It is a sign that in the original data with low signal-to-noise ratio, we were unable to fully resolve residual statics that appears to vary greatly with offset and azimuth. We expect that statics and other parameters can be reliably estimated using beamformed data with the proposed corrections and successfully applied during reprocessing of the original data.

In the second field data example we demonstrate how the proposed approach works with raw dataset acquired in Saudi Arabia using typical 3D orthogonal field acquisition geometry. Figure 4 shows original gather (left), gather after supergrouping (middle) and supergrouping with additional corrections obtained by beamforming approach (right). In this case, shot supergrouping using a spatial aperture of 500 x 200 m or 3 x 5 shots was applied. Each enhanced trace is a stack of 15 original traces. In both cases we observe significant improvements in the signal-to-noise ratio. Additional beamforming corrections better preserve higher frequencies and local details of the events that appear overly smoothed by supergrouping with a simple stack.

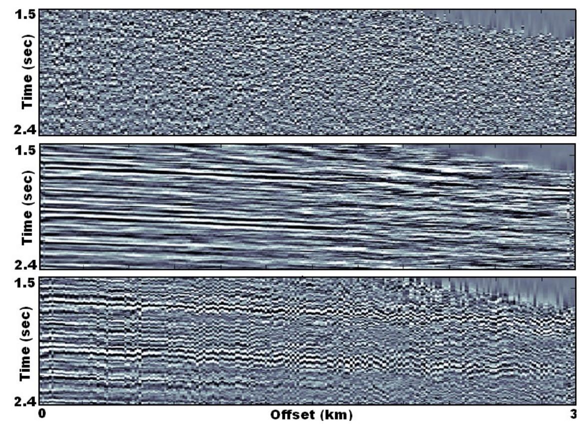


Figure 3: Portions of 3D CDP gather from 3D land data sorted as a function of offset: before enhancement (top), after enhancement using straight summation (middle), and after same enhancement with proposed corrections (bottom). Each enhanced trace is a stack of ~55 original traces.

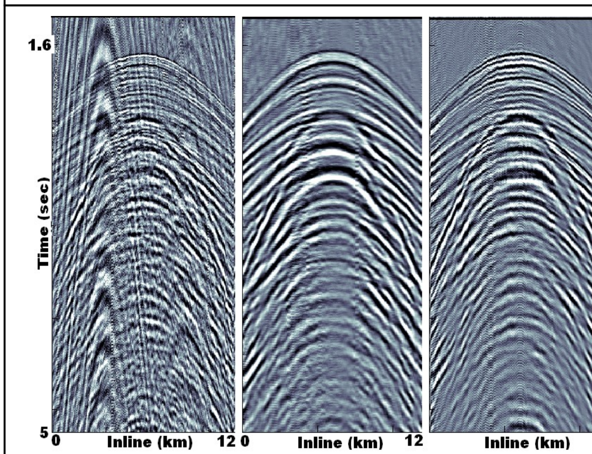


Figure 4: An inline fragment of areal common-shot gather from land 3D data: before enhancement (left), after simple supergrouping 3 x 5 (middle), and after same supergrouping with corrections obtained by beamforming approach (right).

**Conclusions**

We proposed an approach for frequency-dependent phase corrections during supergrouping or any other local summation. It is based on beamforming applied in the STFT domain. Corrections are performed in a "local surface-consistent" manner, i.e., time shifts and phase variations of traces in an ensemble are calculated with respect to a selected reference trace usually located in the middle of the ensemble. The essence of the approach is to extract and enhance the "similarity" in the gathered traces and perform summation. We apply the new approach to supergrouping of shots and receivers. Numerical experiments with synthetic and field data show that these corrections enhance the pre-stack data and preserve localized properties such as statics and waveform variations. We interpret that this beamforming process allows to correct for intra-array statics and residual phase variations, and so leading to preservation of higher frequencies and the ability to robustly estimate local time processing parameters from the enhanced data.

**Acknowledgments**

We would like to thank Saudi Aramco for its support and permission to publish this work.

**EDITED REFERENCES**

Note: This reference list is a copyedited version of the reference list submitted by the author. Reference lists for the 2017 SEG Technical Program Expanded Abstracts have been copyedited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

**REFERENCES**


Bakulin A., P. Golikov, M. Dmitriev, V. Dolgov, P. Leger and D. Neklyudov, 2016, Application of supergrouping to land seismic data in desert environment: 86th Annual International Meeting, SEG, Expanded Abstracts, 4649-4653, http://doi.org/10.1190/segam2016-13838765.1.

Barros, T., M. Covre, A. K. Takahata, and R. Lopes, 2015, Normal moveout with phase equalization: Presented at the 14th International Congress of the Brazilian Geophysical Society & EXPOGEF, Rio de Janeiro, Brazil, 3–6 August, 1306–1311, http://doi.org/10.1190/sbgf2015-259.

Doclo, S., S. Gannot, M. Moonen, and A. Spriet, 2009, Acoustic beamforming for hearing aid application, *in* Haykin, S., and Ray Liu, K. J., eds., Handbook on array processing and sensor networks: John Wiley and Sons, Inc, 269–302.

Freire, S. L. M., and T. J. Ulrych, 1988, Application of singular value decomposition to vertical seismic profiling: Geophysics, **53**, 778–785, http://doi.org/10.1190/1.1442513.

Grion, S., and A. Mazzotti, 1998, Stacking weights determination by means of svd and cross-correlation: 68th Annual International Meeting, SEG, Expanded Abstracts, 1135–1138, http://doi.org/10.1190/1.1820089.

Golikov, P., M. Dmitriev, A. Bakulin, D. Neklyudov, and R. Lakeman, 2015, Improving prestack land data using smart supergrouping: 85th Annual International Meeting, SEG, Expanded Abstracts, 4652–4656, http://doi.org/10.1190/segam2015-5836273.1.

Herman, C., and D. Mace, 1978, The use of the Karhunen-Loeve transformation in seismic data processing: Geophysical Prospecting, **26**, 600–626, http://doi.org/10.1111/j.1365-2478.1978.tb01620.x.

Neklyudov, D., A. Bakulin, M. Dmitriev, and P. Golikov, 2015, Enhancing 3D broadband land seismic data with smart super groups for processing and FWI: 77th Annual International Conference and Exhibition, EAGE, Extended Abstracts, http://doi.org/10.3997/2214-4609.201413435.

Peterson, J. B., and R. D. DeGroat, 1988, Nearly optimal, SVD-based stacking of seismic data: Presented at the 22nd Asilomar Conference on Signals, Systems and Computers, IEEE, 858–862.

Talmon, R., I. Cohen, and S. Gannot, 2009, Relative transfer function identification using convolutive transfer function approximation: IEEE Transactions on Audio, Speech and Language Processing, **17**, 546–555, http://doi.org/10.1109/TASL.2008.2009576.

Trickett, S., 2003, F-xy eigenimage noise suppression: Geophysics, **68**, 751–759, http://doi.org/10.1190/1.1567245.

Ulrych T. J., and M. D. Sacchi, 2005, Information-based inversion and processing with applications: Elsevier, 405.