A FAST MODIFIED PARABOLIC RADON TRANSFORM

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8th January 2010

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ABSTRACT

We present a fast and efficient frequency-domain implementation of a modified parabolic Radon transform (modified PRT) based on a singular value decomposition (SVD) with applications to multiple removal. The method overcomes the heavy computing, required for popular frequency-curvature domain implementations. With a change of variable, the problem is transformed into a complex linear system involving a single operator after merging the curvature-frequency parameters into a new variable. A complex SVD is applied to this operator and the forward modified PRT is computed by means of a complex back-substitution that is frequency-independent. The new transform offers a wider curvature range at most signal frequencies than the other PRT implementations allowing the mapping in the transform domain of low-frequency events with important residual moveouts (long period multiples). Thus the heavy computing required for solving the complex system for each frequency is replaced by faster inversion involving a single complex SVD and a complex back-substitution for each frequency. The method is also capable of resolving multiple energy from primaries when they interfere in a small time interval, a situation where most frequency-domain methods fail to discriminate the different wave types. Additionally, the method resists better to AVO effects in the data than does the iteratively reweighted least-squares (IRLS) method.
The proposed method was successfully applied to a deep-water seismic line in the Gulf of Mexico to attenuate water-bottom multiples and subsequent peg-legs originating from multiple paths in the water column. The suggested technique performs on a similar level as the surface-related multiple attenuation (SRME) in removing residual multiple energy in the stack, but the two approaches can be combined together in the demultiple workflow for the best results.
INTRODUCTION

The Parabolic Radon Transform (PRT) is recognized as a popular demultiplexing tool in seismic processing. The technique relies on the focusing properties of the primary and multiple reflection moveouts in the parabolic Radon domain. The transform can be applied either to common mid-point (CMP) data after stretching the time axis to implement the hyperbolic Radon transform (e.g. Yilmaz, 1989; Sacchi and Ulrych, 1995; Trad et al., 2003), or to seismic data with residual moveouts after the data are corrected for normal moveout corrections (Hampson, 1986; Foster and Mosher, 1992). Hampson (1986) first approximated residual moveouts by parabolic curves and developed the frequency-domain PRT implemented by solving small-size complex-valued inverse problems. Data regularization (interpolation), to fill-in the missing offsets, has been investigated as another application of the transform (Sacchi and Ulrych, 1995; Trad et al., 2002).

Additionally, the smearing problem is common in the standard inversion of the PRT due to limited offset coverage (aperture) and spatial sampling. This directly affects the focusing properties of the transform and degrades the filtering results. Yilmaz (1989), as well as Foster and Mosher (1992), used damped least-squares by means of SVD method to obtain what is known as the regular Radon transform without imposing any constraints in the solution. Methods for constrained inversion were later developed both
in the time (Thorson and Claerbout, 1985; Trad, 2001) and frequency do-

mains (Sacchi and Ulrych, 1995; Cary, 1998; Herrmann et al., 2000; Nowak
and Imhof, 2004) to force the sparseness in the Radon domain using diag-

onial weighting matrices instead of the identity matrix in the least-squares

system and yielded encouraging results for a number of applications. While

the Radon transforms are often recast as inverse problems, a convolutional

approach has been also suggested and the transform can be computed by

means of deconvolving the operator that connects to the transform to pro-

vide the data (Zhou and Greenhalgh, 1994).

The moveout discrimination between the primaries and multiples in the

transform domain is based on the focusing properties of both wave types

in separable regions in the PRT domain. When the separation is good, the

transform can be successfully applied to suppress the multiple energy and

conserve the primaries. However, the presence of noise, amplitude vari-

ations with offsets (AVO), and the failure of the parabolic approximation to

decompose seismic data properly, all affect the focusing properties in the

transform and degrade the demultiple process and affects the reconstructed

primaries. This results in multiple energy mapping into the primary energy

in the Radon model and vice-versa making any filtering difficult. Amplitude

variations with offset along the primaries are often lost after demultiple in

the PRT domain.
Sacchi and Ulrych (1995) proposed a nonlinear algorithm with a sparseness constraint based on a minimum entropy along the curvature direction. The algorithm performs well and leads to a good event focus but fails when dealing with closely separated events in a small time window and when the data exhibits significant AVO effects.

Alternatively, others imposed the time-domain sparseness constraints along both curvature and intercept time directions (Cary, 1998; Schonewille and Aaron, 2007). Weighting matrices are built from the result of the regular transform, or from the obtained model at the previous iteration when the algorithm is iterative. Herrmann et al. (2000) solved for aliasing and aperture artifacts using a constrained minimum-norm under-determined problem with a weighting matrix constructed from the parabolic model obtained at low frequency components. The benefits of the high-resolution time-domain Radon transform over its frequency-domain counterpart have been reported on synthetic and real data examples by Cary (1998) and Schonewille and Aaron (2007). The gain in resolution is due to the fact that the least-squares Radon model has a higher sparseness in the time-domain than in the frequency domain, allowing for a better choice for the weighting matrix for use in the constrained inversion. However, the computing requirements represent a problem with the time-domain implementations especially on
high-fold marine gathers.

The frequency-domain formulation allows for time savings. Thus, the sparse large-size real inverse problem posed in the time domain is replaced by small-size complex systems to solve for all frequency components within the signal bandwidth in the data. Nevertheless, constraints for sparse inversion in the time-domain offer better focus and enhanced multiple removal than their counterparts implemented in the frequency domain. Examples showing this were recently reported by Schonewille and Aaron (2007). Several algorithms were proposed to solve the problem in the frequency domain to increase the resolution and enhance the filtering process.

We present a novel approach for implementing a modified PRT in the frequency domain that allows for faster inversion compared to the frequency-curvature domain PRT and better performance at low frequencies by offering a wider curvature range. Another advantage is computing efficiency where solving several constrained complex inverse problems are replaced by a similar number of inverse problems involving the same operator, thus allowing a significant gain in computing time for the transform. We include under frequency-curvature domain PRT all methods implemented in the frequency-curvature space to compute the transform using standard inversion (least squares) or constrained inversion (using weighting matrices to
force the sparseness in the model). The new transform allows for a wider curvature scan at low frequencies without violating the aliasing conditions compared to frequency-curvature methods which have the same curvature range at all processed frequencies. This can be of great utility when dealing with low frequency events having important residual moveouts which can be mapped easily in the new transform domain, while these are beyond the curvature range allowed by the aliasing conditions in the frequency-curvature methods. In addition, the algorithm has a high performance in discriminating several events having comparable curvature parameters which cannot be resolved using most frequency-domain implementations of the PRT. The proposed method is tested against synthetic examples as well as a real deep-marine data set to attenuate water-bottom multiples and peg-legs with multiple paths in the water layer.

THE MODIFIED PARABOLIC RADON TRANSFORM

The inverse PRT is defined as a decomposition of seismic data in the curvature-intercept time domain using a set of curvature values $q_k, k = 1, N_q$ appropriately chosen to satisfy the requirements of sampling and aliasing. The PRT is defined such that the data are expressed as a sum of constant-amplitude reflections with parabolic moveouts. For discrete seismic data
$D(x_n, t)$ recorded at offset $x_n$ and time $t$, this is defined by a sum along parabolic paths in the $q - \tau$ domain (Hampson, 1986)

$$D(x_n, t) = \sum_{j=1}^{N_q} M(q_j, \tau = t - q_j x_n^2) \quad n = 1, \cdots, N_x, \quad (1)$$

where $M(q, \tau)$ represents the PRT at curvature $q$ and intercept time $\tau$, and $N_q$ being the number of Radon curvatures while $N_x$ denotes the number of seismic traces.

Using the linearity property of the Fourier transform, equation 1 can be expressed in the frequency domain as

$$d(x_n, f) = \sum_{j=1}^{N_q} m(q_j, f) e^{2\pi i q_j x_n^2}, \quad (2)$$

where the temporal Fourier transform $d(f)$ for a function $D(t)$ is defined as

$$d(f) = \int_{-\infty}^{\infty} D(t) e^{2\pi i f t} dt \quad (3)$$

$$D(t) = \int_{-\infty}^{\infty} d(f) e^{-2\pi i f t} df$$

For discrete data, equation 2 is a complex linear system for a given frequency $f$. In matrix notation, this can be written as

$$d(f) = L(f) m(f), \quad (4)$$

where $d(f)$ and $m(f)$ are frequency-dependent vectors. The elements of the matrix $L(f)$ have the form

$$L_{kj}(f) = e^{2\pi i q_j x_k^2} \quad k = 1, \cdots, N_x; j = 1, \cdots, N_q. \quad (5)$$
The above formulation of the PRT requires solving the inverse problem in 4 for each frequency component in the signal bandwidth to compute the transform because the complex operator $L(f)$ is frequency-dependent leading to a different matrix for each spectral component. This system can be solved using a variety of methods (Yilmaz, 1989; Sacchi and Ulrych, 1995; Cary, 1998; Sacchi and Porsani, 1999; Herrmann et al., 2000).

To remove the frequency-dependence in the transform operator $L(f)$, we introduce a new variable $\lambda = qf$ with unit $m^{-2}$. Writing 2 in terms of the variable $\lambda$ leads to the following system of complex equations

$$d(x_n, f) = \sum_{j=1}^{N_q} m(\lambda_j, f) e^{2\pi i \lambda_j x_n^2}.$$  \hspace{1cm} (6)

This can be written in a more compact form as

$$d(f) = L(\lambda) m(f),$$  \hspace{1cm} (7)

where the $N_x \times N_\lambda$ complex matrix $L(\lambda)$ is defined as

$$L_{kj}(\lambda) = e^{2\pi i \lambda_j x_k} \quad k = 1, \cdots , N_x; j = 1, \cdots , N_\lambda = N_q.$$  \hspace{1cm} (8)

Equations 6 or 7 correspond to a modified PRT which can be computed much faster than the frequency-curvature domain PRT because the inverse of the matrix $L(\lambda)$ has to be computed only once, given a data acquisition
geometry $[x_n, n = 1, \cdots, N_x]$ and a chosen discretization $[\lambda_j, j = 1, \cdots, N_\lambda]$. 

The PRT in the frequency-curvature domain, $m(q, f)$, can be obtained by interpolation in the modified PRT domain. The relations between the different transforms are shown in Figure 1 where \textbf{FT} denotes the Fourier transform.

\section*{SAMPLING AND ALIASING}

For a specific seismic data set, the acquisition parameters, $[x_n, n = 1, \cdots, N_x]$, are normally given, and the PRT coordinates, $[\lambda_j, j = 1, \cdots, N_\lambda]$, can be chosen as long as the sampling requirements are fulfilled. Assuming regular sampling, $\Delta x$, in the offset domain and $\Delta \lambda$ in the modified PRT domain, we must have (Hugonnet and Canadas, 1995; Schonewille and Duijndam, 2001)

$$\Delta \lambda < \frac{1}{x_{\max}^2 - x_{\min}^2},$$  \hspace{1cm} (9)

where $x_{\max}$ and $x_{\min}$ are the maximum and minimum offsets in the data, respectively.

In equation 6, the phase difference between the two last expressions must
satisfy, for $\lambda > 0$,

$$2\pi \lambda x_{\text{max}}^2 - 2\pi \lambda [x_{\text{max}} - \Delta x]^2 < 2\pi. \quad (10)$$

This is the case when

$$\lambda < \frac{1}{2x_{\text{max}} \Delta x}. \quad (11)$$

For $\lambda < 0$, we get similarly

$$\lambda > \frac{-1}{2x_{\text{max}} \Delta x}, \quad (12)$$

so that

$$|\lambda| < \frac{1}{2x_{\text{max}} \Delta x}. \quad (13)$$

When the two bounds in inequality 9 and equation 13 are exactly satisfied we have, for $x_{\text{min}} = 0$,

$$N_\lambda = 2 \frac{x_{\text{max}}^2}{2x_{\text{max}} \Delta x} = \frac{x_{\text{max}}}{\Delta x} \approx N_x. \quad (14)$$

Thus the matrix $L(\lambda)$ in equation 7 can, in principle, be inverted. It is, however, numerically ill-conditioned, and a stabilized solution (as shown later) must be used.

In standard seismic data, the curvature values are normally positive. In order to reduce the $\lambda$– range we must partly NMO-correct the data, so there are reflections with negative and positive curvatures. Then by observing
the minimum moveout in the data, $\Delta T_{\text{min}}$ (which maybe negative), and the maximum moveout, $\Delta T_{\text{max}}$, we can limit the range of $\lambda-$values to

$$\lambda_{\text{min}} = \frac{\Delta T_{\text{min}} f_{\text{max}}}{x_{\text{max}}^2} < \lambda < \frac{\Delta T_{\text{max}} f_{\text{max}}}{x_{\text{max}}^2} = \lambda_{\text{max}},$$

(15)

where $f_{\text{max}}$ is the maximum signal frequency in the data. $\lambda_{\text{min}}$ and $\lambda_{\text{max}}$ must, of course, satisfy inequality 13 above.

For a high resolution modified PRT, we choose a relatively small sampling interval, $\Delta \lambda$, satisfying inequality 9 (Herrmann et al., 2000; Schonewille and Aaron, 2007). The number of values in the PRT domain,

$$N_\lambda = \frac{\lambda_{\text{max}} - \lambda_{\text{min}}}{\Delta \lambda},$$

(16)

is then normally larger than the number of seismic channels $N_x$.

A vertical line in the $q - f$ domain corresponds to an event with a parabolic moveout parameter ($q = \text{constant}$) in the time-offset domain. In the $\lambda - f$ domain this gives a radial line defined by the equation $\lambda = qf$. Keeping this in mind, all operations in the $q - f$ domain can also be done in the $\lambda - f$ domain. We also note that from $\lambda = qf$, the range in $q-$ values for low frequencies is larger than for high frequencies. This means that the modified PRT has better curvature coverage at low frequencies than the frequency-curvature domain PRT. Low frequency events with important parabolic moveouts may violate aliasing conditions in the frequency-
curvature domain PRT, whereas these can be appropriately mapped in the \( \lambda - f \) domain thanks to a wide curvature range allowed by the transform (figure 2b). The standard and modified PRT’s have the same curvature range only at the maximum signal frequency \( f_{\text{max}} \). For smaller frequencies, the modified PRT has a wider curvature range providing better coverage in the curvature domain at most signal frequencies (Figure 2). The red rectangle in figure 2a represents the covered curvature zone in the frequency-curvature domain PRT according to the sampling rules (Turner, 1991; Schonewille and Duijndam, 2001). The larger zone shows the curvature range covered by the sampling relations for the modified PRT method expressed by equation 13. This shows a curvature range that is inversely proportional to the processed frequency, thus allowing the mapping of low frequency events in the \( \lambda - f \) domain even for important curvature (figure 2b). The red area in this figure shows the equivalent \( \lambda - \) space highlighted according to the sampling rules in the standard PRT. In fact, the two red regions in the \( q - f \) and the \( \lambda - f \) domains are equivalent and show the limited coverage in the standard PRT at most signal frequencies. Correspondingly, the \( \lambda - \) sampling interval, \( \Delta \lambda \), is inversely proportional to the processed frequency, thus keeping the same number of \( \lambda - \) values for each frequency. This does not affect the performance of the modified PRT, but artefacts will appear at low frequencies when computing the standard transforms, either \( q - f \) or \( q - t \) domains, is required. In fact, only a limited \( \lambda - \) range is used to recover the correspond-
ing $q-f$ domain in response to the aliasing conditions. The benefits from
this additional curvature range are important when multiples with large
residual moveouts are input for removal. In such a case, the standard PRT
may not map all the events in the frequency-curvature domain, while this
can be handled by the modified PRT. Examples include multiple reflections
with several paths in the water layer for deep water seismic surveys which
exhibit large residual moveouts compared to primaries flattened along the
offset axis. For most cases, the new domain, $\lambda-f$, allows to perform de-
multiple based on moveout discrimination between primaries and multiples
as well as data interpolation avoiding the need to the abovementioned in-
terpolation (see the flowchart in Figure 1). This interpolation is required if
separation of parabolic events in a seismic gather requires a dynamic $q-f$
or $q-t$ rejection zone that cannot be implemented directly in the $\lambda-f$ space.

The least-squares solution

We want to solve the linear problem in equation 7 when the number of
seismic channels, $N_x$, is larger than the number of values in the $\lambda$-domain,
$N_\lambda$. Then the problem is overdetermined and the least-squares solution can
be written as

$$ m_{LS}(f) = [L^H(\lambda)L(\lambda)]^{-1}L^H(\lambda)d(f), \quad (17) $$

where $H$ denotes the complex conjugate transpose (the adjoint operator). It
is well known that computing this expression as written may give numerical
problems due to the large condition number of the matrix $L^H(\lambda)L(\lambda)$.

Instead we use the singular value decomposition (SVD) (Björck, 1996)

$$L(\lambda) = U \begin{bmatrix} \Sigma \\ 0 \end{bmatrix} V^H,$$  \hspace{1cm} (18)

where $U$ and $V$ are complex unitary matrices and $\Sigma = \text{diag}[\sigma_1, \sigma_2, \cdots, \sigma_{N\lambda}]$ with $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_{N\lambda} \geq 0$.

A stable least-squares estimate is given by

$$m_{\text{LS}}(f) = V \begin{bmatrix} \Sigma^+ \\ 0 \end{bmatrix} U^Hd(f),$$  \hspace{1cm} (19)

where $\Sigma^+$ is the pseudo-inverse of $\Sigma$ with components

$$\sigma_k^+ = \begin{cases} \sigma_k^{-1} & \text{if } \sigma_k \geq \epsilon, \\ 0 & \text{if } \sigma_k < \epsilon, \end{cases}, \quad k = 1, \cdots, N\lambda.$$  \hspace{1cm} (20)

Truncated SVD is used to exclude small singular values while computing the pseudo-inverse. The numerical rank is often greater than the mathematical rank of $L(\lambda)$ due to rounding errors during computations. We define the mathematical rank of a given matrix as the number of rows or columns linearly independent. Using the decomposition 18, the mathematical rank denotes the number of non-zero singular values of the matrix. The null singular values (numerically very small) reside in the null-space domain of the matrix. Equation 20 assigns a numerical rank to $\Sigma$ and hence to $L(\lambda)$ by
moving the small singular values into the null space of \( \mathbf{L}(\lambda) \) (Björck, 1996).

Alternatively, one may use a damped least-squares stabilization with

\[
\sigma_k^\dagger = \frac{\sigma_k}{\sigma_k^2 + \epsilon}, \quad k = 1, \cdots, N, \tag{21}
\]

where \( \epsilon \) now is a damping parameter. This stabilization reduces the condition number from \( \sigma_1/\sigma_N \) to a smaller value.

With \( \tilde{\mathbf{m}}_{LS}(f) = \mathbf{V}^H \mathbf{m}_{LS}(f) \) and \( \tilde{\mathbf{d}}(f) = \mathbf{U}^H \mathbf{d}(f) \), equation 19 gives

\[
\tilde{\mathbf{m}}_{LS,k}(f) = \begin{cases} 
\sigma_k^\dagger \tilde{d}_k(f) & k = 1, \cdots, N \\
0 & k = N + 1, \cdots, N_x
\end{cases}. \tag{22}
\]

It is seen that the components \([\tilde{d}_k, k = N+1, \cdots, N_x]\) do not contribute to the solution.

**The minimum-norm solution**

In a high-resolution modified PRT, we choose the number of \( \lambda \)-values, \( N_\lambda \), to be larger than the number of seismic channels. Then the problem is under-determined and we choose the minimum-norm solution (Björck, 1996) which can be written as

\[
\mathbf{m}_{MIN}(f) = \mathbf{L}^H(\lambda) \left[ \mathbf{L}(\lambda) \mathbf{L}^H(\lambda) \right]^{-1} \mathbf{d}(f). \tag{23}
\]
We use the SVD decomposition for the operator $\mathbf{L}(\lambda)$

$$\mathbf{L}(\lambda) = \mathbf{U}[\Sigma \ 0]\mathbf{V}^H,$$  \hspace{1cm} (24)

where $\Sigma = \text{diag}[\sigma_1, \sigma_2, \cdots, \sigma_N]$ with $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_N \geq 0$, to obtain a stable estimate

$$\mathbf{m}_{\text{MN}}(f) = \mathbf{V} \begin{bmatrix} \Sigma^\dagger \\ 0 \end{bmatrix} \mathbf{U}^H \mathbf{d}(f),$$ \hspace{1cm} (25)

where $\Sigma^\dagger$ is the pseudo-inverse of $\Sigma$ as defined in equation 20 or, alternatively, in equation 21.

The transformations $\tilde{\mathbf{m}}_{\text{MN}}(f) = \mathbf{V}^H \mathbf{m}_{\text{MN}}(f)$ and $\tilde{\mathbf{d}}(f) = \mathbf{U}^H \mathbf{d}(f)$ gives

$$\tilde{\mathbf{m}}_{\text{MN},k}(f) = \begin{cases} \sigma_k^\dagger \tilde{\mathbf{d}}_k(f) & k = 1, \cdots, N_x \\ 0 & k = N_x + 1, \cdots, N_{\lambda}. \end{cases} \hspace{1cm} (26)$$

We see that the last components of $\tilde{\mathbf{m}}_{\text{MN}}$ are zero, corresponding to the minimum-norm properties of the solution $\mathbf{m}_{\text{MN}}$.

**MULTIPLE ATTENUATION AND DATA REGULARIZATION**

We may attenuate multiple reflections in the $\lambda - f$ domain by partly correcting the seismic data for normal moveout effects such that the primary reflections appear with less moveout than multiples. The main assumption
on seismic data input to the transform is that residual moveouts of both primary and multiple reflections have parabolic behavior as a function of offset (Hampson, 1986). The data are transformed to the $\lambda - f$ domain using an inverse operator

$$\hat{m}(f) = L^\dagger(\lambda)d(f),$$

(27)

defined in equation 19 or 25. An estimate of the primary reflections is obtained by filtering the data $\hat{m}_p(f) = F(\lambda, f)\hat{m}(f)$ where the filter is

$$F(\lambda, f) = \begin{cases} 1 & \text{for } \lambda \leq q_0 f \\ 0 & \text{for } \lambda > q_0 f \end{cases},$$

(28)

where $q_0$ is a curvature parameter that separates primaries and multiples in the $\lambda - f$ space. The primary reflections are then obtained by transforming back to the $x - f$ domain

$$d_p(f) = L(\lambda)F(\lambda, f)L^\dagger(\lambda)d(f) = G(\lambda, f)d(f).$$

(29)

The matrix $G(\lambda, f) = L(\lambda)F(\lambda, f)L^\dagger(\lambda)$ has dimensions $N_x \times N_x$. It behaves as a filter applied to seismic data in the frequency-offset domain to remove multiples directly from the data. The multiples can be also estimated using the following relationship

$$d_M(f) = [I_{N_x \times N_x} - G(\lambda, f)]d(f).$$

(30)

where $I_{N_x \times N_x}$ is the identity matrix.
For a given frequency, the operator $G$ depends only on the data acquisition parameters, our choice of parameters in the $\lambda$-domain, and the choice of parameters for the pseudo-inverse.

Radon transforms are an attractive domain for data interpolation to fill in the missing offsets or to output a data set with a regular offset sampling from an input gather where acquisition conditions didn’t allow to achieve such a purpose (Trad et al., 2002). Regularization is also required when data are input to some processing programs such as the frequency-wavenumber filtering, some migration algorithms, and surface-related multiple elimination (SRME). This can be done by the modified PRF from

$$\tilde{d}(f) = \tilde{L}(\lambda)\tilde{m}(f) = \tilde{L}(\lambda)L^\dagger(\lambda)d(f),$$  \hspace{1cm} (31)

where $\tilde{L}(\lambda)$ is defined as in equation 8, but the points $[x_n, n = 1, \cdots, \tilde{N}_x]$ are the desired offsets after interpolation. The points $[\lambda_j, j = 1, \cdots, N_\lambda]$ are the same in $\tilde{L}(\lambda)$ as in $L(\lambda)$. $\tilde{N}_x$, being the number of channels in the interpolated data set. We may even combine the two algorithms to attenuate multiples and interpolate data at the same time

$$\tilde{d}_{PF}(f) = \tilde{L}(\lambda)F(\lambda, f)L^\dagger(\lambda)d(f).$$  \hspace{1cm} (32)

In all these cases there is, for each frequency, a multiplication by a fixed matrix which transforms data from the $x-f$ domain to the $\lambda-f$ domain.
NUMERICAL RESULTS

Synthetic data

1. Constant-amplitude events

To test the efficiency of the novel approach over popular methods, we investigated a complex synthetic data example that consists of a large number of events (20 parabolas) interfering in a narrow time window as illustrated in Figure 3a. This model contains 12 primaries (Figure 3b) and 8 multiples (Figure 3c). The primaries are characterized by negative curvature values whereas the multiples have positive curvatures. This situation can be produced by applying normal moveout corrections using a velocity law between the stacking velocities of the primaries and those of the multiples. There are $N_x = 100$ seismic channels with offset spacing $\Delta x = 0.02 km$ and a maximum offset $x_{max} = 2.0 km$. From equations 9 and 13 we obtain the bounds $\Delta \lambda < 0.25 km^{-2}$ and $|\lambda| < 12.5 km^{-2}$.

The moveout at the maximum offset used to compute the transform is in the range $\Delta T \in [-0.3s, 0.3s]$. With a maximum signal frequency $f_{max} = 60 Hz$, this gives from equation 15 $\lambda \in [-4.5 km^{-2}, 4.5 km^{-2}]$ which is within the maximum value computed above. In Figure 4, we have computed the singular values for the matrix $L(\lambda)$ for different values of $N_{\lambda}$ (or equivalently $\Delta \lambda$) with a fixed range of $\lambda$. 
For $N_\lambda = 50$ (the curve in black), the inverse problem in 7 is overdetermined ($N_x > N_\lambda$) and the condition number is small ($\sigma_1/\sigma_{50} = 3.11$). In this case, the least-squares inverse operator $L^{-1}(\lambda)$ can be computed, but the transform is not able to map appropriately the primary and multiple modes for accurate filtering due to poor sampling along the $\lambda$-axis. For $N_\lambda = N_x = 100$ (the curve in grey), the operator $L(\lambda)$ is a square matrix, but the condition number is large ($\sigma_1/\sigma_{100} = 1.34 \times 10^9$). In this case, damping or truncation is required to estimate a pseudo-inverse for the operator $L(\lambda)$ and compute the transform. The curve for a finer sampling rate, $N_\lambda = 250$, is shown in the same figure in dashed line and corresponds to an under-determined problem. The general tendency for the three curves is that the decrease in singular values of $L(\lambda)$ is slow up to about half the number of seismic traces before a rapid drop to vanishing singular values

$[\sigma_k \simeq 0 \text{ for } k = N_x/2 + 1, \ldots, \min(N_x, N_\lambda)]$. We used the minimum-norm solution which converts the problem into an inverse problem of dimension $N_x \times N_x$ as provided by equation 25. The SVD of the minimum-norm operator gives an infinite condition number for $N_\lambda = 250$. To compensate for this, the pseudo-inverse in equation 20 was used with $\epsilon = 10^{-3}$. The complex operator $L(\lambda)$ presents the property of rank deficiency regardless the size of the operator, the range of curvatures and offsets. About half of the singular values of $L(\lambda)$ are mathematically zero (numerically very small).
and do not contribute into the solution as they belong to the null-space of $L(\lambda)$. When $N_\lambda < \frac{N_x}{2}$, the operator $L(\lambda)$ has a small condition number and no truncation is required to compute the transform, but the expected resolution in the $\lambda - f$ domain is not achieved leading to poor demultiple and data interpolation results. The parameter $\epsilon$ in equation 20 defines the limit between singular values used to compute the new transform and those belonging to the null space and assumed to be mathematically zero. The presence of the null space explains a linear dependence between rows and columns of $L(\lambda)$ making the computation of the transform an ill-conditioned inversion problem when $N_\lambda > \frac{N_x}{2}$.

The mapping of the whole gather in Figures 3a in the $\lambda - f$ domain is shown in Figures 3d. Primary and multiple energy are mapped in distinct areas of the $\lambda - f$ domain. Each event with a parabolic moveout in the time-offset domain is transformed along a radial line in the $\lambda - f$ domain passing through the origin and characterized by the respective event curvature as the slope value and with a frequency content shaping the wavelet spectrum. According to this, events with positive curvatures ($q > 0$) are mapped into the positive $\lambda$-space while negative $\lambda$-space contains events with $q < 0$. Events in the time-offset domain having the same curvature value overlap within their spectra and their transforms add constructively in the $\lambda - f$ space.
The filtering is applied following a constant $q$-value to separate the events in the original gather according to their curvatures as provided by the relation 28. Since primaries have negative curvatures in the example, a mute zone was established at $q = 0$ (corresponding also to $\lambda = 0$) to separate primaries and multiples, as shown in Figures 3e and 3f, respectively. The reconstructed gathers after inverse transform are shown in Figures 3g, 3h, and 3i, they show the events in the original gather with their true curvature and amplitude characteristics. The reconstruction errors for the three gathers are depicted in Figures 3j, 3k, and 3l. This error is very small for the whole gather and is mainly due to the use of truncation in estimating the pseudo-inverse of $L(\lambda)$. All PRT methods suffer such residual errors after reconstruction due to the ill-conditioning of the inverse problem. The residual errors from separating primaries and multiples show opposite signs on the gathers. This occurs mainly along the axis $\lambda = 0$ thus generating horizontal low-amplitude artifacts in the filtered gathers.

2. Events exhibiting AVO effects

To examine the relative merits of the novel approach when the data exhibit AVO effects, we included amplitude variations with offset in the example of Figure 3. The amplitude functions introduced along the primary and multiple moveout curves are second-order functions in normalized offset given
by

\[ A(y) = a_0 + a_1 y + a_2 y^2; \quad y = \frac{|x|}{x_{\text{max}}}, \]  

(33)

where \( y \) is the normalized offset. \( a_0, a_1, \) and \( a_2 \) are real coefficients that describe the amplitude functions along the events. The parameter \( a_0 \) represents the intercept of the AVO function, while \( a_1 \) and \( a_2 \) denote the amplitude gradient and curvature in the offset domain, respectively.

Figures 5a, 5b, and 5c depict the gathers in Figures 3a, 3b, and 3c after AVO effects were included along the parabolic moveouts on individual events according to equation 33. The amplitude effects on the 12 primary events (in Figure 5b) are plotted in Figure 6 (curve in black). The amplitude plots of the events are ordered with respect to increasing zero-offset time of the primaries, row by row and column by column in Figure 6. These show significant amplitude changes with normalized offset and several zero-crossings can be observed. The coefficients \( (a_0, a_1, \) and \( a_2) \) are given on each plot for the respective event. The event interference between primaries and multiples and between primaries alone leads to amplitude distortion on individual events in the gather. Thus, the amplitudes of the events being interfered add to each other within the crossing area, hence altering the AVO curve and making the amplitude inversion inaccurate. The green curves in Figure 6 show the practical amplitude functions for each event of the primaries that accounts for the interference with the other primaries. Outside the interef-
ence zone, the theoretical and practical amplitude curves are equal.

The results of applying the modified PRT algorithm to the gather including such AVO effects are given in Figure 5 and the recovered amplitude functions of the primaries after demultiple are also drawn in Figure 6 (curves in blue). Figure 5d shows the \( \lambda - f \) mapping of the gather in Figure 5a. With a mute zone applied at \( \lambda = 0 \), the primary and multiple mappings in the modified PRT domain are plotted in Figures 5e and 5f, respectively. The events in the original gathers are transformed into the linear trends in the \( \lambda - f \) domain showing much similarity with Figure 3 where the same gathers were considered without AVO effects. The reconstructed gathers, depicted in Figures 5g, 5h, and 5i, preserve the amplitude variations, showing that this method is an alternative to other frequency-domain algorithms requiring removal of the AVO effects (using sliding gain functions for instance) before the transform is applied. The residual errors after reconstruction are very small for the entire gather (Figure 5j) and show again the low-amplitude horizontal artifacts (Figures 5k and 5l) similar also to the first example (constant-amplitude events).

Schonewille and Zwartjes (2001) proposed a sparseness-constrained frequency-domain algorithm resisting well to AVO effects, where the weighting matrix is obtained by averaging the model within the signal bandwidth at the pre-
vious iteration to constrain the solution at the current iteration. Their method can be implemented using the iteratively reweighted least-squares (IRLS) algorithm combined with a complex version of the LSQR solver. The approach proposed by Schonewille and Zwartjes (2002) is explained in the Appendix. Both algorithms give comparable results, but the modified PRT algorithm has the advantage to be much faster.

The amplitude curves recovered from applying the frequency-domain sparseness constrained inversion method are shown by the red curve in Figure 6 for the 12 events after a single iteration. From the curves, we observe that both methods provide a good reconstruction of the practical amplitude functions along the primaries at most offsets despite the strong interference in the treated example. The recovered amplitudes are very accurate at most offsets. At medium offsets, $0.2 \leq y \leq 0.9$, the suggested approach allows for more accurate conservation of the AVO curve than does the IRLS method. At near offsets ($y < 0.2$), the IRLS method has generally smaller amplitude errors but the error is larger than the modified PRT for some primaries (events 6 and 7 for instance). The same observation can be made at very far offsets ($y > 0.9$) where the IRLS method performs slightly better. The proposed method proves higher accuracy in amplitude recovery than the IRLS approach at most offsets. This observation is further confirmed on Figure 7 which depicts the average absolute amplitude error for the 12 events in Fig-
Figure 5b. The superiority in performance of our approach (blue curve) is again demonstrated except at the extreme offsets in the data. The black and green curves in Figure 7 show the absolute errors of the AVO function using 2 and 5 iterations in the IRLS approach, respectively. With further iterations in the IRLS method, increased accuracy is achieved at most offsets. However, a loss of accuracy can also be observed at intermediate offset ranges when comparing results after 2 and 5 iterations. There is a significant reduction of the errors associated with most offsets than the first iteration (red curve) but these errors still larger than the modified PRT errors at most offsets which has the added advantage to be very fast.

Figure 8 illustrates the method when the data exhibit AVO effects and contain random noise. Such a situation is very common on real data and can affect the performance of the transform. For most algorithms, accounting for AVO effects using a gain function will magnify noise and degrade the reconstruction and the separation abilities of the transform. The results shown in Figure 8 show that the modified PRT method stills perform well in such a complicated model. In the $\lambda - f$ domain, the recognition of the radial lines mapping the events is still possible despite the presence of noise in the data. We used for this example a larger value for the truncation level $\epsilon = 2.2 \times 10^{-2}$ to avoid noise amplification in the $\lambda - f$ domain and in the separated gathers. The filtered primaries exhibit AVO responses approxi-
mating those in the original model, and the reconstruction error has only residual noise and the artifact with a zero curvature (at \(q = 0\)). As the residual noise resides in the small singular values of the operator \(L(\lambda)\), this is altered after reconstruction either by damping or truncation. This explains why the reconstruction error of the gather in Figure 8a is dominated by noise (Figure 8j).

The Mississipi Canyon seismic line

The modified PRT method was tested on a marine seismic line from the Gulf of Mexico. The area is characterized by a deep sea-bottom with important amplitude variations with offset and water-bottom multiples. The data was tested by several demultiple programs due to the complexity of the model (Dragoset, 1999; Guitton and Cambois, 1999; Hadidi et al., 1999; Lamont et al., 1999; Lokshtanov, 1999; Verschuur and Prein, 1999; Trad et al., 2003). Figure 9b shows the gather at location CMP 500 and illustrates the strong interference in the area and the large number of events recorded. Nonhyperbolic velocity analysis was performed on the data to generate post-NMO data to be input for the modified PRT algorithm. Due to the thick water layer, (1.4km to 1.5km), and the thin layers following, moveout velocities are very low (mostly ranging from 1500 to 2000 m/s). A velocity spectrum computed using the semblance coefficient is given in Figure 9d for this gather.
The decrease of stacking velocities after 4s is an obvious indicator of the presence of water-bottom multiple reflections and peg-legs originating from the layers just below the sea-bed. No primary energy can be recognized on the velocity spectrum at late times (> 4s) due to the presence of multiple reflections masking any primary reflections from a deep salt body in the model. To flatten primary reflections at far offsets, we scanned for both the moveout velocity and effective anellipticity parameters to obtain more accurate NMO corrections. AVO variations were accounted for in nonhyperbolic velocity analysis using sliding gain functions which allowed the picking of the reflected energy in the gathers. Figure 9c shows the gather after applying nonhyperbolic NMO corrections with parameters derived from automatic velocity analysis (Abbad et al., 2009). The primary energy corrected with the exact moveout parameters (moveout velocity and effective anellipticity) is well flattened in the full offset range, whereas multiple energy has positive residual moveouts that can be well approximated using parabolic curves as observed in the lower part of the gather after 4s (Figure 9c). The stretched area around time 2.7s in the NMO-corrected gather is due to the strong interference in the original gather at far offsets which can be observed also at a larger time on the gather before moveout corrections depicted in Figure 9b.

The data acquisition parameters are described in detail in Verschuur and Prein (1999). The offsets range from 0.1km to 4.874km with a maximum
CMP fold equal to $N_x = 90$. The data were processed in the time range $[1.6s - 7.0s]$, limited to the region below the sea bottom where reflections are recorded. The modified PKT was applied to the NMO-corrected data in Figure 9c with a moveout range $\Delta T \in [-0.05s, 0.7s]$ at the maximum data offset. Negative moveout values were included to account for primaries possibly overcorrected at far offsets. Using a maximum signal frequency $f_{\text{max}} = 60Hz$, this gives $\lambda \in [-0.127km^{-2}, 1.79km^{-2}]$. The last value is just below the limit $|\lambda| < 1.89km^{-2}$ according to equation 13. Figure 10 shows the distribution of singular values of the matrix $L(\lambda)$ in equation 8 for different values $N_\lambda = 45, 90$ and 225. For $N_\lambda = 45$ the range of variations in the singular values is small, but for $N_\lambda = 90$ and $N_\lambda = 225$ the singular values become very small after the 45 first singular values. Again, there is a sharp drop in the singular values around $N_x/2$ $[(\sigma_k \simeq 0$ for $k = N_x/2 + 1, \cdots, N_\lambda)]$. We use $N_\lambda = 225$ and a minimum-norm solution in equation 25 with a cut-off value $\epsilon = 5 \times 10^{-2}$ in equation 20 to compute the modified PKT. This gives the transformed data shown in Figure 9a. The multiple reflections are filtered out with a cut-off line defined by $\lambda > q_0 f$ chosen such that

$$\lambda > \frac{\Delta T_0 f}{x_{\text{max}}^2},$$

(34)

where $\Delta T_0 = 0.1s$ is the cut-off value for the moveout at the maximum offset, $x_{\text{max}}$. This gives the transformed primaries and multiples shown in Figures 9e and 9i, respectively.
The data gathers corresponding to these domains are computed through equation 7 and are illustrated in Figures 9g and 9k. Inverse nonhyperbolic moveout corrections are applied to reconstruct the original gathers filtered into primary (Figure 9f) and multiple (Figure 9j) reflections. These gathers show that multiples are concentrated in the lower part of the gather due to multiple paths in the water-column and peg-legs in subsequent thin layers below the sea-bed. The velocity spectra for the filtered primaries and multiples are respectively depicted in Figures 9h and 9l. After demultiple, significant primary energy is recovered after 4s and can be clearly recognized in the primary gather (Figure 9f) and also in the corresponding velocity spectrum (Figure 9h).

Figure 11 shows the stack obtained from automatic nonhyperbolic velocity analysis (Abbad et al., 2009) without any demultiple. The stack illustrates the main features of the area mainly a deep salt body at around recording time 5s. The lower part of the stack is dominated by important multiple reflections after 3.5s with multiple paths in the water layer and peg-legs in the layers beneath the sea-bottom. The application of the surface-related multiple elimination (SRME) algorithm to this seismic line is illustrated in Figure 12 (from Verschuur and Prein, 1999). The same plotting scale and parameters for nonhyperbolic moveout corrections were
used as in Figure 11. As this method requires data regularization, the PRT method was used as part of the SRME method to fill in the near missing offsets in the data which increases the implementation time of the method. The obtained stack after demultiple via the SRME shows improved quality in the lower part of the section with most multiple energy being removed. However, residual multiples can be clearly observed between 4 and 5s.

The application of the modified PRT method to this data is illustrated in Figure 13. The result shows efficient removal of the associated multiple energy in the data. In the upper part of the section, the result is better than the SRME method, because the method allowed the removal of peg-legs coming after the reflection from the water bottom which enhanced the continuity of the shallow reflectors in the section. However, residual multiples still observable around time 4.5s in the stack. The modified PRT was applied with the parameters derived for the single CMP gather shown in Figure 9. As suggested by Hadidi et al. (1999), the modified PRT method was also applied to the data after the SRME method (as shown in Figure 12). The resulting stack shown in Figure 14 is clearly the best in terms of removing multiple reflections in the data.

**COMPUTATIONAL COST**

Both the modified PRT and the constrained PRT based on the IRLS method
work in the $x-f$ domain. This requires $2N_x$ FFT’s of length $N_f$ ($= 2^k \geq N_t$, $k$: integer) for both methods. For multiple attenuation with the modified PRT as given in equation 29 there will be additional $N_{fo}$ (number of discrete frequencies) multiplications with the $N_x \times N_x$ complex matrices $G(\lambda, f)$. For the IRLS approach there will additionally be $N_{fo}$ complex inversions times the number of iterations of the system given in (A-3) which increases significantly the computing time since each system involves a different matrix for any processed signal frequency. The computing times of the two algorithms depend mainly on the number of processed frequencies and on the CMP fold.

Table 1 summarizes the CPU timing for the modified PRT and the sparseness constrained PRT based on the IRLS method, according to tests on a Pentium IV platform. The reported times confirm the considerable gain in computing time in the modified PRT algorithm. The IRLS method has larger computing requirements becoming heavy if several iterations are necessary. This is the case when the amplitude functions need to be conserved in view of a subsequent AVO inversion. For the whole line, the demultiple process requires about 51 min for the modified PRT and almost 6 hours for a single iteration of IRLS if amplitude conservation is a relevant issue of the processing sequence. The timing results show that the modified PRT is about six to eight times faster than the IRLS method.
CONCLUSIONS

A fast implementation of a modified parabolic Radon transform has been proposed. The transform is linked to the frequency-curvature domain PRT by means of interpolation, but the proposed transform can serve as a fast and efficient tool for multiple removal and data interpolation without the need to build the transform in the curvature-time or the curvature-frequency domains. The algorithm is very fast for marine seismic gathers having the same streamer geometry. If the processing parameters for the parabolic Radon filtering are the same for these gathers, the pseudo-inverse operator for the minimum-norm solution can be saved in memory and the modified PRT panel is obtained for each CMP gather by means of complex back-substitution only. This has advantages over frequency-domain algorithms requiring saving the same operators in memory for each spectral component to expect similar time saving (Trad et al., 2003).

The synthetic and real data examples for multiple attenuation showed that the new method is six to eight times faster than a PRT method based on the iteratively reweighted least-squares (IRLS) inversion method. The Mississippi Canyon data example showed that optimum multiple suppression was obtained by applying the SRME algorithm followed by the modified PRT method.
ACKNOWLEDGEMENTS

The authors thank WesternGeco for making available the Gulf of Mexico data set and Eric Verschuur for sharing the results from the SRME algorithm on this data set. This project received financial support from the Norwegian University of Science and Technology (NTNU), PetroMax, the Federal University of Bahia (UFBA), CNPq, StatoilHydro ASA through the VISTA project, and the Norwegian Research Council through the ROSE project.
Appendix A

AMPLITUDE-COMPENSATED SPARSENESS-CONSTRAINED TRANSFORM IN THE FREQUENCY DOMAIN

The iteratively reweighted least-squares (IRLS) is an inversion method for solving $l^p$-norm minimization problems when $1 \leq p \leq 2$, thus lying between the least absolute-values ($p = 1$) and the least-squares ($p = 2$) solutions. The cost function for a constrained problem in the least-squares sense can be expressed as

$$S(m) = \| Lm - d \| + \epsilon m^H W_m^{-1} m,$$  \hspace{1cm} (A-1)

where $W_m$ is a weighting matrix used for preconditioning the model space. It is chosen to impose some desired features in the model (sparseness or smoothness for instance), and $\epsilon$ is a damping factor. The minimization of the cost function in (A-1) can be translated into solving the complex system of equations

$$\begin{bmatrix} L & 0 \\ \xi^{1/2} W_m^{-1/2} & 0 \end{bmatrix} \begin{bmatrix} m \\ 0 \end{bmatrix} = \begin{bmatrix} d \\ 0 \end{bmatrix}.$$  \hspace{1cm} (A-2)

We apply a left-preconditioning to the model $m$ and a right-preconditioning to the operator $L$ with the weighting matrix $W_m$, so the system in (A-2) can be written as
\[
\begin{bmatrix}
\tilde{L} \\
\xi^{1/2} \mathbf{I}
\end{bmatrix}
\begin{bmatrix}
\tilde{\mathbf{m}} \\
\mathbf{d}
\end{bmatrix} = \begin{bmatrix}
\mathbf{d} \\
\mathbf{0}
\end{bmatrix}
\quad \text{where} \quad \tilde{L} = L W_m^{1/2} \quad \tilde{\mathbf{m}} = W_m^{1/2} \mathbf{m}.
\]

The problem in (A-3) is first solved for the preconditioned model \(\tilde{\mathbf{m}}\) before recovering the true model \(\mathbf{m}\) by removing the effect of \(W_m\). The weighting matrix \(W_m\) is chosen such that

\[
W_{m,k} = |m_k|^{(2-p)/2}.
\]

The least-squares solution \((p = 2)\) is thus a special case where the weighting matrix is set to identity.

Recently, Ji (2006) proposed a solution to the \(p\)-norm minimization problem using weighting matrices for both model and residual vectors implemented using the IRLS method via a modified version of conjugate gradients. Several choices for designing the weighting matrices for the model \(m\) have been proposed (Sacchi and Ulrych, 1995; Cary, 1998; Herrmann et al., 2000; Nowak and Imhof, 2004) with the aim to boost components in the complex model \(m\) that contain information about the events in the gather. These are defined from the computed model at the previous frequency component. Schonewille and Zwartjes (2001) proposed, instead, an iterative process with a number of outer loops to refine the solution. Inner loops are aimed at solving the preconditioned problem in (A-3) using a weighting
matrix that depends on the obtained model at the previous frequency for the first iteration. For the first iteration, the weighting matrix we used in the paper examples is given by

\[
W_{m,k}(f_j) = \frac{|m_k(f_{j-1})|}{\max|m(f_{j-1})|}, \quad \text{for } f_j \geq f_{\text{min}}, \quad k = 1, \cdots, N_q. \tag{A-5}
\]

This gives a frequency-dependent weighting matrix for the first outer loop for frequencies inside the signal bandwidth. No weighting is used for frequencies outside this domain \((W_m = I)\) which corresponds to the least-squares solution. For an iteration \(i > 1\), the PRT domain is computed using a weighting matrix \(W_m\) that is the average of the models obtained in the signal bandwidth at the previous iteration \(i-1\) (Schonewille and Zwartjes, 2001)

\[
W_{m,k}^{(i)} = \frac{1}{n_f \max|\mathbf{m}_k|^{(i-1)}} \sum_{j=1}^{n_f} |\mathbf{m}_k(f_j)|^{(i-1)}, \tag{A-6}
\]

where the number between parentheses in the superscript denotes the iteration index. The system \((A-3)\) is solved in an iterative manner by changing the weighting matrix at each iteration to impose more sparseness in the solution. We used the complex version of the subspace solver LSQR to solve the preconditioned problem in \((A-3)\) given a weighting matrix. The system can be equally solved via complex conjugate gradients where the number of internal iterations serves as a regularization factor for the solution (Trad et
al., 2003). Except for the first iteration, the weighting matrix is frequency-independent and is obtained by the averaging in (A-6).
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<td>Modified PRT</td>
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<tr>
<td>Synthetic example</td>
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<td>Real data (2180 CMP’s)</td>
<td>51 min 03 s</td>
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