Weighted stacking of up- and down-going RTM images using peak signal-to-noise ratio analysis

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SUMMARY

This work introduces a new method for improving seismic imaging in deepwater environments by combining reverse time migration (RTM) images using peak signal-to-noise ratio (PSNR) analysis. The proposed approach exploits local PSNR values as similarity/dissimilarity weights to combine RTM-generated seismic images of up-going primaries and down-going (water-bottom-related multiples) wavefields. The local PSNR emphasizes areas of similarity between RTM images and indicates where the correlation is most pronounced, increasing the accuracy and quality of subsurface representations. The deepwater Brazilian pre-salt case study using ocean bottom node (OBN) data reveals the effectiveness of the proposed method in highlighting geological features and reducing artifacts. The results also indicate that the fusion of primary and mirror RTM images guided by PSNR enhances the delimitation and definition of subsurface structures, offering a promising solution for improving seismic imaging in deepwater oil and gas exploration.

INTRODUCTION

Deepwater oil and gas operations have experienced significant growth in the last years, despite inherent great challenges (Motta et al., 2020). Deepwater (and ultra-deepwater) seismic recordings using ocean bottom sensors can generate two independent subsurface images by analyzing up-going (primary reflections) and down-going (first multiples in the water layer) wavefields separately. Although up-going and down-going waves illuminate the subsurface in different ways, the resulting seismic images should be equivalent in regions illuminated by both types of wavefields. In this context, combining seismic images obtained from the primary and mirror reverse time migration (RTM) methods, where matching sections are enhanced and discordant regions are suppressed, can result in a more accurate subsurface representation.

Weighted stacking strategies have played a crucial role in several geophysical applications. Liu et al. (2009) studied a stacking procedure that uses local correlation as a weighting factor. The study demonstrated enhancements in the signal-to-noise ratio and image quality of seismic data, reducing random noise and artifacts, particularly for profiles with limited fold coverage. Hatchell et al. (2012, 2015) showed that using a weighted combination of up-going and down-going migrations may effectively reduce time-lapse (4D) noises. Yang et al. (2022) analyzed the effects of six stacking metrics on different onshore and offshore seismic arrays to improve signal quality and reduce contamination. These developments highlight the significance of improving stacking methods for the most effective geophysical analysis.

In this work, we present a new way to stack RTM images obtained by evaluating up-going and down-going wavefields from the same seismic recordings. Besides, we analyze field data collected from an ocean bottom node (OBN) survey in the deepwater Brazilian pre-salt area (Duarte et al., 2023; da Silva et al., 2024) to demonstrate the efficacy of our proposal. The proposed strategy relies on the peak-signal-to-noise ratio (PSNR), a robust quality metric commonly utilized in image processing (Najafipour et al., 2013). PSNR serves as a discriminating tool, emphasizing areas of similarity between images and indicating where the correlation is most pronounced. In particular, we consider a local PSNR analysis to identify regions of high structural similarity between primary and mirror RTM images at a pixel level. The final seismic image is obtained through PSNR-weighted stacking of the primary and mirror RTM images.

THEORY

Up-going and down-going wavefields

Deepwater oil field exploration involving ocean bottom nodes (OBN) or ocean bottom cables (OBC) allows for the creation of (at least) two independent images of the same subsurface area. This is accomplished by independently employing the traditional up-going wavefield and the down-going wavefield through mirror migration techniques. The up-going wavefield primarily captures primary reflections, providing insights into shallow subsurface features, while the down-going wavefield, consisting notably of multiples, extends the imaging capabilities to encompass deeper geological structures. Various subsurface areas are accessed by both primaries and water-bottom-related multiples, resulting in redundant data from identical reflectors. Figure 1 depicts how up-going primary waves (magenta dashed line) and down-going first-order multiples waves (red line) arrive at a node on the ocean floor from air gun sources at the surface of the water. Down-going waves exhibit an extra reflection at the air-water interface (free surface), of-

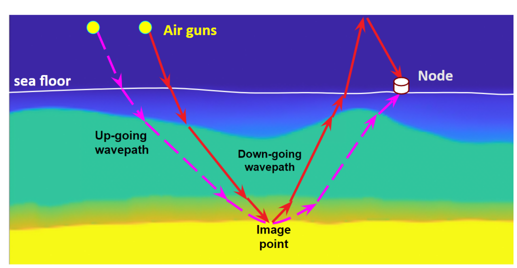

Figure 1: Illustration of up-going primaries (magenta dashed line) and down-going first-order multiples (red line) waves. Seismic waves fired from air gun sources at the sea surface, illuminating a point of interest for imaging. (Figure adapted from Hatchell et al. (2012))

fering more information than primary waves.

The migration of up-going and down-going wavefields faces challenges in accurately imaging subsurface structures. In the context of sparse node geometry, up-going imaging is incapable of capturing the vicinity of the seafloor, whereas down-going imaging is impacted by artifacts caused by cross-talks resulting from interference among unrelated multiples (Zhang et al., 2020). Therefore, integrating up-going and down-going wavefields presents an attractive solution to improve the resolution and coverage of seismic images, contributing to a more robust characterization of deep-water reservoirs.

PSNR-weighted stacking of RTM images

Peak Signal-to-Noise Ratio (PSNR) is a metric commonly used to evaluate image quality that helps identify peaks by highlighting minimal differences between images (Najafipour et al., 2013). PSNR is sensitive to differences between image pixels, so peaks in consistent regions between images have higher values, indicating greater similarity.

Given $I_U = [u_{ij}]_{m\times n}$ and $I_D = [d_{ij}]_{m\times n}$ the matrix representation of the RTM images generated from up-going and down-going waves, respectively, the PSNR between I_U and I_D, expressed in terms of decibels (dB), is defined by:

$$\mathrm{PSNR}(I_U, I_D) = 10 \cdot \log_{10}\left(\frac{p_{max}^2}{\mathrm{MSE}(I_U, I_D)}\right), \quad (1)$$

where $p_{max} = \max(I_U, I_D) = \max\left(\max_{i,j} u_{ij}, \max_{i,j} d_{ij}\right)$ represents the maximum absolute value that a pixel can have in RTM images I_U and I_D (maximum fluctuation in the images) and MSE stands for mean square error and is defined as:

$$\mathrm{MSE}(I_U, I_D) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(u_{ij} - d_{ij}\right)^2, \quad (2)$$

with u_{ij} and d_{ij} denoting the pixel value at the i,j coordinates.

When comparing two RTM images, higher PSNR values signify areas of congruence, where peaks align, thus indicating a greater degree of similarity. PSNR and MSE are inversely proportional, indicating that as the difference between images I_U and I_D decreases (lower MSE), the PSNR value increases. In addition, due to the logarithmic scale relationship, a minor reduction in MSE will lead to a significant rise in PSNR.

The PSNR coefficient (1) only provides one value for the whole RTM image. However, our focus is on highlighting local geological features instead of global ones. To achieve this, we define a matrix of PSNR weights, $S_{\mathrm{PSNR}} = [s_{ij}^{\mathrm{PSNR}}]_{m\times n}$, derived from sliding-window PSNR coefficients (or local PSNR), in which its elements are obtained through:

$$s_{ij}^{\mathrm{PSNR}} = 10 \cdot \log_{10}\left(\frac{p_{max_{i,j}}^2}{\mathrm{MSE}(I_{\hat{U}_{i,j}}, I_{\hat{D}_{i,j}})}\right), \quad (3)$$

where $I_{\hat{U}_{i,j}} \subset I_U$, $I_{\hat{D}_{i,j}} \subset I_D$, $p_{max_{i,j}} = \max\left(\max_{k,l} u_{kl}, \max_{k,l} d_{kl}\right)$ with $(k,l) \in (i - q_i : i + q_i, j - q_j : j + q_j)$ represents the maximum absolute value of a rectangular region centered on (i, j) with width $(2q_i + 1)$ and $(2q_j + 1)$ in the row and column directions, and

$$\mathrm{MSE}(I_{\hat{U}_{i,j}}, I_{\hat{D}_{i,j}}) = \sum_{k=i-q_i}^{i+q_i}\sum_{l=j-q_j}^{j+q_j}\frac{\left(u_{kl} - d_{kl}\right)^2}{(2q_i + 1)(2q_j + 1)}. \quad (4)$$

To illustrate, consider the points in Fig. 2(a) as pixels of a discretized RTM image. To evaluate the similarity between I_U and I_D in the red point, a sampling is initially carried out around it, that is, sub-images ($I_{\hat{U}_{i,j}}$ and $I_{\hat{D}_{i,j}}$) are taken out from the original RTM images (see green points in Fig. 2(b)). Then, the sampled points from I_U are compared with the equivalently sampled points from I_D. Then, the PSNR coefficient for the chosen vertex is calculated using Eq. (3). Finally, this process is repeated for all points in the RTM images, thus building the matrix of PSNR weights, $S_{\mathrm{PSNR}} = [s_{ij}^{\mathrm{PSNR}}]_{m\times n}$.

Furthermore, to avoid possible exorbitant values associated with PSNR coefficients, we define a weight matrix W expressing the set of obtained PSNR values on a relative scale, rather than absolute values:

$$W = \frac{|S_{\mathrm{PSNR}}|}{\max(|S_{\mathrm{PSNR}}|)}, \quad (5)$$

where $\max(|S_{\mathrm{PSNR}}|) = max_{i,j}\ |s_{i,j}^{\mathrm{PSNR}}|$ denotes the maximum value of the whole matrix $|S_{\mathrm{PSNR}}|$ and $|\cdot|$ represents the absolute value. The elements of W range from 0 to 1, with a value near 1 representing strong structural similarity and a value near 0 representing no structural similarity. In this way, we define the resulting RTM model (I_{W}) weighted by PSNR through the point-wise operations

$$I_{\mathrm{W}} = \left(I_U \oplus I_D\right) \odot W, \quad (6)$$

where $\oplus$ and $\odot$ represent, respectively, the element-by-element sum and product operations. Equation (6) represents the final model obtained by combining the traditional primary and mirror RTM images through stacking with the weight W (5).

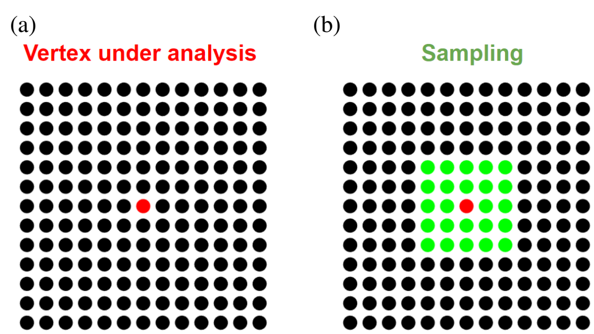

Figure 2: Illustration of the sampling process to evaluate the similarity between two images I_U and I_D at a specific point. (a) Points considered as pixels of a discretized RTM image, where a point of interest is indicated in red. (b) Sampling around a point of interest with sub-images taken out from the original RTM images (depicted by the green points).

CASE STUDY

To validate the efficacy of the proposed approach in stacking primary and mirror RTM images, we consider a P-wave velocity model retrieved via the full-waveform inversion (FWI) methodology. This analysis was conducted within the context of a deepwater Brazilian pre-salt field, utilizing OBN hydrophone real dataset (with a 50m shot grid) (da Silva et al., 2021). Please refer to the study conducted by our team in da Silva et al. (2023, 2024) to learn more about the mentioned OBN acquisition and FWI analysis. Since primary and water-bottom-related multiples waveforms are well highlighted and, for the most part, remarkably isolated (da Silva et al., 2023), we separate the receiver-gathers into up-going and down-going pressure wavefields. Then, for this work, we apply a 0–15 Hz band-pass filter (0–1–14–15 Hz, Ormsby filter). We construct velocity models and RTM images in a 3D setting. However, for simplicity, we only consider one slice of the seismic cube in this work. Although our focus is on combining 2D seismic images, it is important to note that our proposal can readily adapt to 3D scenarios.

Figure 3 shows the weight operator, in which the colors represent the normalized local PSNR defined by Eq. (5). The brightness color falls steadily from 0 to 1, where 0 indicates no similarity and 1 indicates high similarity. The area with the most significant seismic illumination (post-salt zone, 2-3 km deep) is associated with the highest weights, enabling for a clear depiction of the top of the salt body. Additionally, varying weight values are noticeable in the pre-salt region (6–8 km deep). We compute the local PSNR by analyzing samples containing 121 elements ($q_i = q_j = 5$), representing a square region surrounding the place of interest with a width of 250 m.

We employ an RTM technique that relies on the inverse scattering imaging condition. This imaging condition is based on inverse scattering theory concepts and helps reduce artifacts generated by undesirable cross-correlations (Yang and Zhang, 2022), such as backscattered waves, that might arise in the stacking process, which may occur with the classical imaging condition. We consider a seismic source estimated following the methodology described in Pratt (1999) and an acoustic modeling engine in the time domain.

Figures 4(a) and 4(b) show, respectively, the primary and mirror 15 Hz RTM images. It can be seen in the primary RTM image (Fig. 4(a)) that the up-going primary wavefield is not efficient for the geometry of the sparse nodes to generate images of the shallower subsurface structures. This is because the primaries are unable to reach the shadow zones for illumination, as discussed in Pacal et al. (2015). In contrast, the water-bottom-related multiples can penetrate the subsurface in order to illuminate shadow areas, generating more faithful seismic images of shallow regions ($\approx$ 2–3 km deep), as can be seen in the post-salt region as depicted in Fig. 4(b).

Figure 4(c) shows the RTM image resulting from the weighted combination between the primary and mirror RTM images (Figs. 4(a) and 4(b)) using Eq. (6). It is noticeable that combining primary and mirror RTM images using the PSNR-based factor improves the resulting RTM image in various ways. The significant enhancement in identifying the bottom of the salt body is crucial for characterizing the top of deep presalt reservoirs. Additionally, there is a notable improvement in defining salt stratification. Moreover, the proposed strategy can emphasize somewhat discernible pre-salt layers in the initial RTM images. Thus, the proposed similarity stack approach can enhance the continuity of geological strata, producing a more unified seismic image of subsurface features.

Figure 5 shows zoomed views of the enclosed regions (blue, magenta and green lines) within the RTM images depicted in Fig. 4. The first, second, and third columns represent RTM images of up-going (primary) waves, down-going (water-bottom-related multiples), and the local PSNR-based metric. The pro-

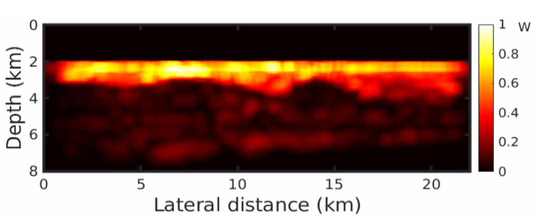

Figure 3: PSRN-based weight operator. Weight operator map depicting local PSNR values.

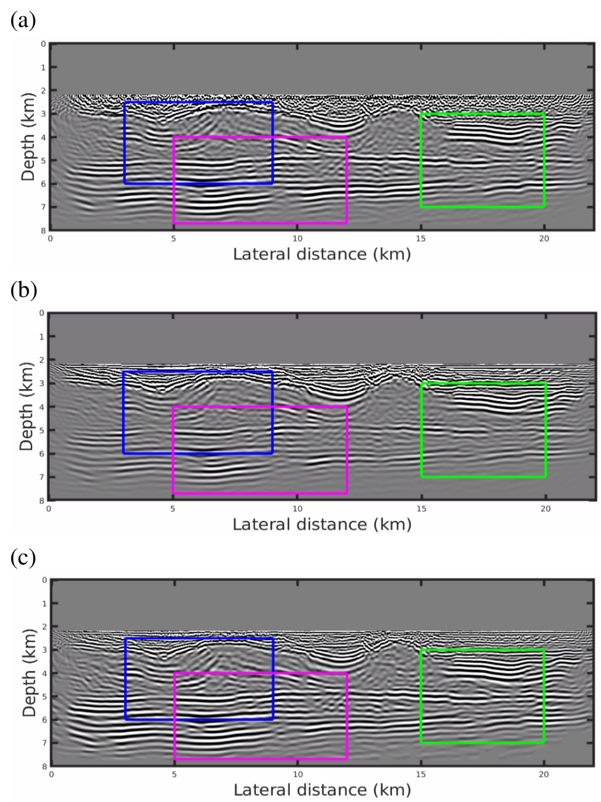

Figure 4: Resulting migrated images. RTM images of (a) up-going primary waves, (b) down-going (water-bottom-related multiples), and (c) from the weighted fusion of primary and mirror RTM images. We scale the color of all RTM images using the 95th percentile.

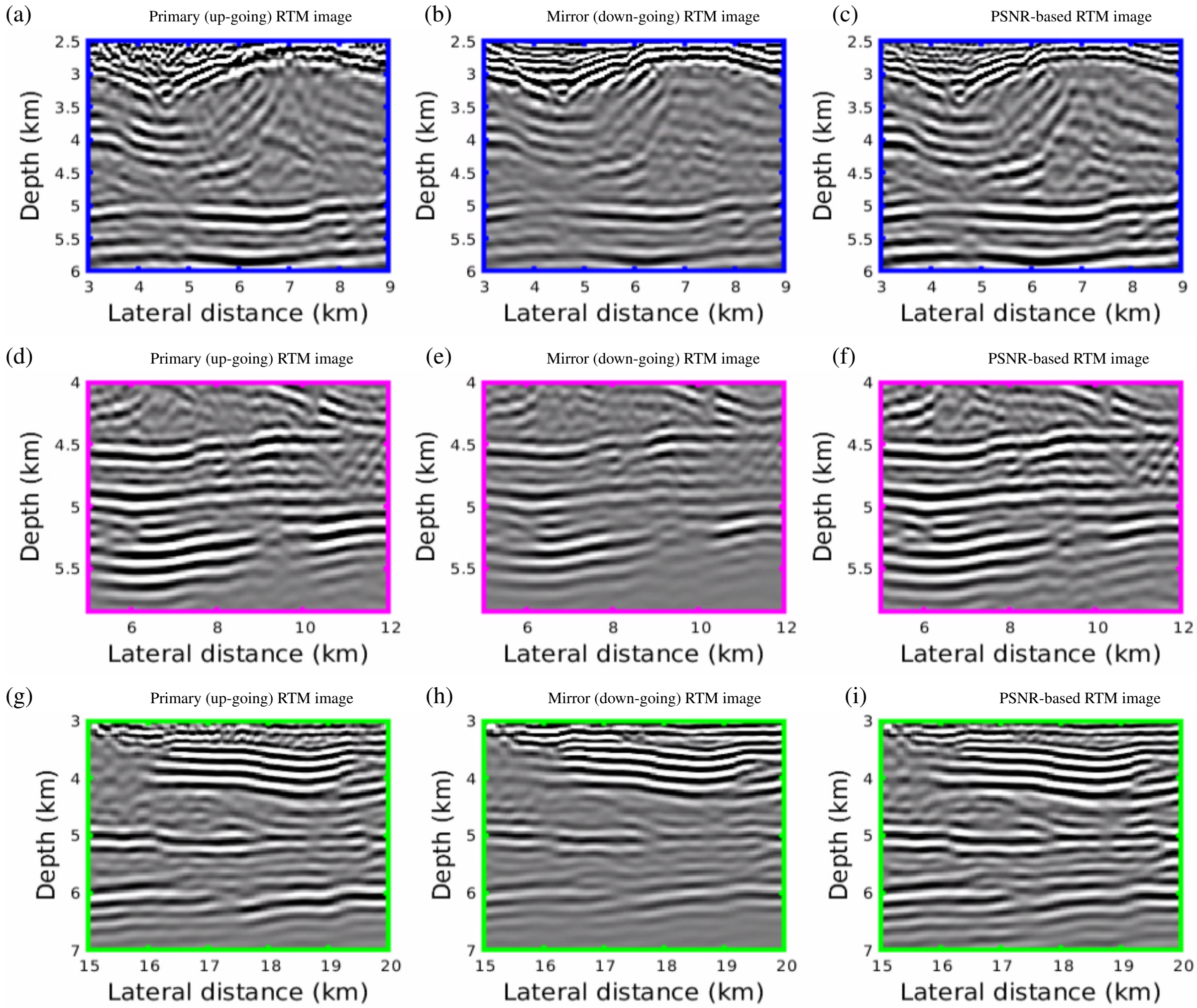

Figure 5: Zoomed-in views of various areas of the migrated images presented in Fig. 4. The first, second, and third columns correspond, respectively, to RTM images of up-going waves, down-going), and the local PSNR-based metric.

posed strategy improved the delineation of structures like the top salt ($\approx$ 2.5–3.5 km deep) and significantly enhanced the definition of salt stratification ($\approx$ 3.5–4.5 km deep), as can be noted by comparing Figs. 5(a), 5(b) and 5(c). Furthermore, the proposed similarity stack approach improves the visibility of the continuity of the geological strata at the bottom of the salt body ($\approx$ 5 km deep) and the structures of the deep pre-salt reservoirs (see, for instance, the layers around 6 km deep in Figs. 5(d), 5(e) and 5(f)), further emphasizing discernible pre-salt layers in the initial RTM images, as depicted in the $\approx$ 6–7 km deep area of Figs. 5(g)-5(i)).

FINAL REMARKS

In this work, we have introduced a weighted stacking method for combining up-going and down-going RTM images using local peak signal-to-noise ratio (PSNR) analysis to improve the quality and precision of seismic imaging in deepwater settings. The deepwater Brazilian pre-salt case study revealed that by combining seismic images obtained from different wavefields using a weighted operator based on local PSNR values, a more detailed seismic subsurface representation is achieved, particularly in regions illuminated by both types of wavefields. The proposed method can emphasize key characteristics of the subsurface layers, such as the top of salt bodies, deep pre-salt reservoirs, and salt stratification, with improved clarity and continuity. As a perspective, we intend to look into how sensitive the final RTM image is to the sample size used in the local PSNR analysis, since the sample size can change the similarity analysis between the primary and mirror RTM seismic images.

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