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Deblending of multi-source Seismic Data Based on Dual-Element Attention Mechanism Network

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ABSTRACT

The high-density blended acquisition technology effectively improves the acquisition efficiency in seismic exploration, but it requires addressing the aliasing problem of its acquired data, known as the deblending problem. Among numerous deblending methods, deep learning-based denoising has gained increasing attention and research from scholars in recent years due to its efficiency in handling complex aliased data and the advantage of not requiring manual adjustment of numerous parameters. Given the complexity of blended data and the correlation between source signals, a DeamNet network incorporating a Dual-Element Attention Mechanism is proposed to achieve blended data separation. This Dual-Element Attention Mechanism can effectively extract the features of blended data for complex multi-source blended datasets, allowing for the retention of more valid signals during deblending, facilitating subsequent imaging processing. To verify the deblending performance of the DeamNet network, numerical experiments were conducted using both synthetic and real data, and its performance was compared with DnCNN and U-Net, both of which have also been applied in the deblending field in recent years. The final comparison results confirmed the effectiveness of the DeamNet network in deblending.

KEYWORDS

High-density multi-source blended acquisition; Multi-source blended data; Deep Learning; Deblending; Dual Element-wise Attention Mechanism

Since the concept of blended excitation acquisition technology was first introduced, this highly efficient, low-cost acquisition technique has attracted widespread attention from professional researchers and oil companies [1-4]. In traditional seismic acquisition, to avoid time-domain overlap of seismic data, the time interval between adjacent sources must either be increased, or the spatial interval between adjacent sources must be enlarged. The former results in low acquisition efficiency and high costs, while the latter leads to low coverage, thereby degrading data quality. High-density blended acquisition, however, does not need to consider time-domain overlap, making it more efficient and cost-effective than traditional seismic acquisition [2].

The data obtained through high-density blended acquisition is called blended acquisition data. Due to the signal overlap from multiple sources, the imaging methods for blended acquisition data can be classified into two categories: direct imaging and separation followed by imaging [5-8]. The direct imaging method introduces cross-talk noise in the migrated profiles due to the coherence of signals from different traces, affecting the imaging accuracy [9]. Therefore, this paper focuses on the separation-then-imaging method, which solves the problem of signal separation in blended acquisition data, enabling high-precision imaging.

Common deblending methods include filtering [10-13], inversion [14-17], deep learning denoising techniques, etc. Among them, traditional deblending algorithms based on filtering and inversion primarily rely on the selection of parameters, such as filter length, type of sparse transform, and corresponding thresholds. These parameters are typically chosen based on personal experience through repeated experimentation and may vary depending on the dataset, requiring fine-tuning in practice. Additionally, for multi-dimensional and high-resolution blend seismic data, the computational cost of traditional deblending algorithms increases significantly [2]. On the other hand, deep learning denoising techniques enable automated deblending without the need for manual adjustment of numerous parameters. Moreover, deep learning methods can effectively capture the features of more complex blend seismic data through deep network structures, thereby enhancing deblending performance. Consequently, research on deep learning denoising methods for blend data separation has grown in recent years.

For example, Zu, Sun, and others studied intelligent deblending using CNNs [3-4]. Zu et al. embedded an iterative framework into a pre-trained network. To reduce the dependence on training data, they introduced an iterative strategy and transfer learning to enhance deblending performance [18]. A physics-enhanced deep learning method for blend seismic data deblending was proposed for iterative workflows, which does not require collecting large amounts of labeled data [19]. Wang used a UDL network, which combines residual neural networks and U-Net, for blend data deblending [2], solving the challenge of acquiring blend labeled data. Compared to these methods, the DeamNet network used in this paper, based on a dual-element attention mechanism, focuses on processing complex seismic data and can preserve more effective signals while deblending multi-source blend overlap.

Since there is a strong correlation between effective signals in blend acquisition data, and signals from different sources within the same shot line also exhibit strong similarity, the dual-element attention mechanism, which combines spatial and channel-wise attention processing, can not only focus on local details but also enhance the relationships between feature channels.

1 Pseudo-separation

In the process of high-density blended acquisition, the blended acquisition data in the time domain can be represented as:

$$P_{bl} = P\Gamma \tag{1}$$

Where P_{bl} is the blended acquisition data, P is the single-source data to be separated, and the Γ is constructed based on the delay time of each shot. Since the number of blended shots is smaller than the number of single shots, the Γ in an underdetermined matrix. Γ^{-1} does not have an exact solution but can only be constructed via a pseudoinverse, given by the following equation:

$$\Gamma^{-1} = (\Gamma^{\mathrm{H}}\Gamma)^{-1}\Gamma^{\mathrm{H}} \tag{2}$$

Where Γ^{H} is the transpose of Γ, and by combining equations (1) and (2), we can obtain:

$$P^{*} = P_{bl}\left(\Gamma^{\mathrm{H}}\Gamma\right)^{-1}\Gamma^{\mathrm{H}} \tag{3}$$

Where P^{*} is the pseudoseparated seismic data, also referred to as the pseudodeblended data.

Due to the differences in excitation times between multiple sources, the blended acquisition data are continuous for all sources in the common shot point domain. However, in other domains such as the common receiver point domain, common offset domain, and common center point domain, only the data from the primary source remain continuous, while the data from other sources become discrete [20]. The method of converting the blended acquisition data from the common shot point domain to other domains, thereby making the data from other sources discrete, is called pseudoseparation. The data obtained after pseudoseparation is referred to as pseudodeblended data [21].

2 DeamNet

The DeamNet network was first introduced by Ren Chao, Wang Chunchen, and others in their 2021 paper on image denoising [22]. This network utilizes Adaptive Consistency Priors (ACP) and a dual-element attention mechanism, which can better identify image features and reconstruct image details. The network structure is shown in Figure 1, and Figure 2 illustrates the sub-network module in Figure 1.

2.1 Adaptive Consistency Prior

Adaptive Consistency Prior (ACP) is a prior constraint technique used to enhance the performance of neural networks, especially in cases where data is scarce or uncertainty is high. The core idea is to introduce a consistency constraint that guides the model to better follow certain prior knowledge or patterns during the learning process, thereby improving the model's stability, generalization ability, and robustness.

Since real blend acquisition data is difficult to obtain, and in blend acquisition data, local continuity, non-local self-similarity, and strong correlations are often present simultaneously in both local and non-local areas, this paper chooses to use the DeamNet network with consistency priors to achieve deblending of blend data based on these characteristics.

The formula for consistency prior is as follows:

$$J_{CP}(X) \overset{def}{=} \sum_{i=1}^{n} \|x_i - \sum_{j\in D_i} \omega_{ij}\, x_j\|_2^2 \tag{4}$$

Where $X\in\ R^{\mathrm{n}}$ represents an image containing n pixels, $x_i$denotes the i-th element of the image, D_i denotes the index vector of pixels related to x_i in x, x_i and x_j are the normalized weights of ω_{ij}.

For ease of discussion, write (4) as follows:

$$J_{\mathrm{CP}}(X) = \|I(X - MX)\|_2^2 \tag{5}$$

③① ②①

Where $I\in\ R^{\mathrm{n}\times\mathrm{n}}$ is an identity matrix, and $W\in\ R^{\mathrm{n}\times\mathrm{n}}$ is a diagonal consistency matrix composed of $\omega_{ij} - s$. The consistency prior can be understood as follows: the image X in the pixel domain (denoted as ①) is first filtered by the linear consistency matrix W (denoted as ②), and then the magnitude of the fitted deviation vector $(X - WX)$ is uniformly constrained by I (denoted as ③). The adaptive consistency prior in DeamNet is improved as follows:

Use a function $T(\cdot)$to convert $X$to a high-dimensional space, which is more conducive to the recovery of image features.

Use adaptive and nonlinear filtering functions $K(\cdot)$ instead W to prevent the linear similarity matrix W from smoothing image details too much.

Replace I with the reliability matrix Λ to constrain $(X - WX)$, thus obtaining the new adaptive consistency prior:

$$J_{CP}(X \mid \underbrace{T,K,\Lambda}_{\text{pre-specified}}) \stackrel{\text{def}}{=} \|\Lambda(T(X)-K(T(X)))\|_2^2 \tag{6}$$

Then we use Taylor expansion to approximate simplification, plus a penalty term $\psi(X|Y,T) = \|\mathcal{Y} - \mathcal{X}\|_2^2 (\mathcal{Y} = T(Y))$

The denoising algorithm based on ACP is obtained:

$$\hat{X} = \arg\min_X \psi(X|Y,T) + \lambda J^*_{ACP}(X|T,K,\Lambda) \tag{7}$$

Among them, the $\hat{X}$ is predicted clean image. λ is the regularization parameter $(\lambda > 0)$,Since $K(\cdot)$ 、Λ and $T(\cdot)$ have been preset before optimization, the only unknown variables is X.

In order to accurately estimate clean images $\hat{X}$, how to pre-design the best one of $\{K(\cdot), \Lambda, \lambda, T(\cdot)\}$ is a key issue.

DeamNet is an end-to-end trainable network based on this problem, which can learn these operators adaptively.

2.2 Dual Element-wise Attention Mechanism

The Dual Element-wise Attention Mechanism is an attention mechanism that enhances the ability of neural networks in feature extraction and information processing. This mechanism applies attention in both spatial and channel dimensions, which can effectively improve the ability of the model to capture key information, making the model more efficient in handling complex tasks. In the blended mining data, the effective signals have strong correlation, and the effective signals also have great similarity between different seismic source data of the same gun line. Therefore, DeamNet using the two-element attention mechanism can better extract the characteristics of the effective signal, and retain the effective signal to the greatest extent while deblending. Spatial Attention: By analyzing the spatial dimensions of the input features, the spatial attention mechanism identifies the spatial locations in the data that are important to the current task. For example, in blended data, spatial attention can help the model focus on the key areas of the valid signal and ignore other unimportant parts. Channel Attention Mechanism: The channel attention mechanism focuses on the channel dimension of the feature map and analyzes the importance of each channel in expressing different categories or attributes. Through the channel attention mechanism, the model can assign higher weights to important channels, thus prioritizing task-related features.

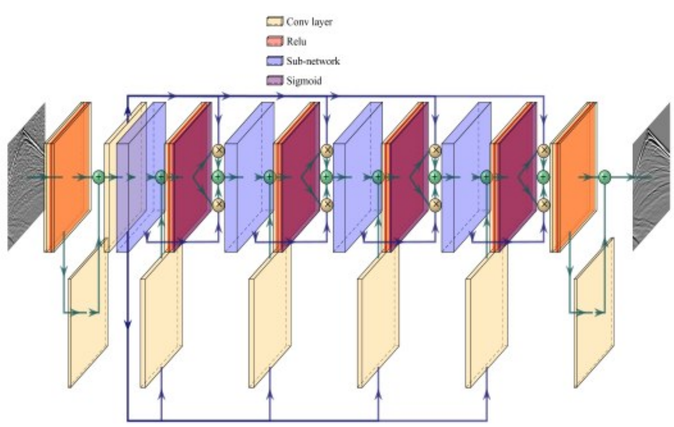

Figure 1 DeamNet network structure diagram

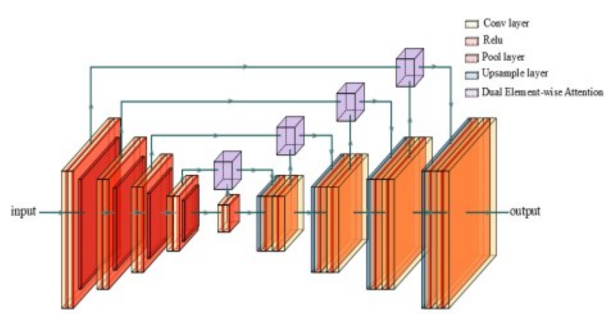

Figure 2 Sub-network structure diagram

3 Testing

In order to verify and measure the deblending effect of the DeamNet network, this paper selects the convolutional residual network (DnCNN) [1] [23-24] and the semantic segmentation network (U-Net) [2] [18] [21] [25] [26], which have been used in the field of multi-source seismic deblending and have good deblending effect, to compare with the DeamNet network in synthetic data and real data respectively.

3.1 Testing of synthetic data

The geological model uses the Marmousi-II model, the model size is 5 × 4 km2, a total of 300 detection points and 300 seismic sources are set, the receiver and seismic source are located 20m underground, the track spacing and gun spacing are set to 15m, and the seismic record length is 3.6s.

To test the deblending effect of DeamNet on three-source synthetic data, a total of three shotline data were generated. Each of the three shotlines was then multiplied by a random time-delay operator and blended to obtain the three-source blended.

Figure 3 shows the deblending effects of three networks on the three-source blended acquisition data, and Table 1 lists the training results of the three networks. For the three-source pseudo-deblended data with more noise (Figure 3), we find that the errors after deblending by DnCNN and U-Net clearly show signal loss (Figure 3f, g). In contrast, the loss of effective signals after deblending by DeamNet is significantly less (Figure 3h). Therefore, the results in Figure 3 prove that DeamNet has better deblending capabilities than DnCNN and U-Net on three-source pseudo-deblended data.

Analyzing Table 1, we find that although DeamNet is not as efficient in training as DnCNN and U-Net, it has a stronger deblending capability. Combining the results of Figure 3, it can be seen that the stronger deblending capability of DeamNet is reflected in its ability to retain more effective signals, which is beneficial for subsequent processing of the separated single-source data.

Table 1 Quantitative evaluation criteria for deblending effect of seismic blended mining data based on three different network structures

network name	Minimum Loss	peak signal-to-noise ratio(PSNR/dB)	Training time/s
DnCNN	231.9034	49.8904	1123
U-Net	183.5077	49.9074	718
DeamNet	101.0065	52.7631	5753

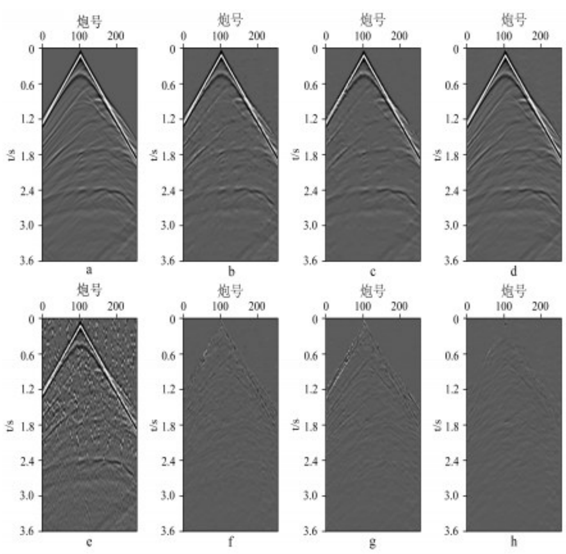

Figure 3 Blending results and errors of three-source blended mining data

a unblended seismic data; b results of DnCNN deblending; c results of U-Net deblending; d results of DeamNet deblending; e three-source blended data; f errors between DnCNN deblending results and clean data; g errors between U-Net deblending results and clean data; h errors between DeamNet deblending results and clean data

3.2 Testing of actual data

This paper uses the actual data in the southern part of Beihai to test the deblending effect of DeamNet. The actual data in the southern part of Beihai contains a total of 101 gun data, the number of detectors is 120, the acquisition time is 3 seconds, and the sampling interval is 2 ms. As shown in Figure 4, the unblended single source data in the common gun domain and the common receiver domain and the blended dual source blended data are shown respectively.

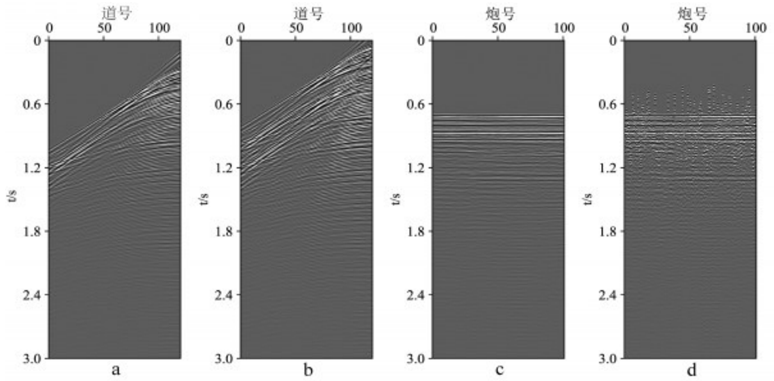

Figure 4 Actual seismic data before and after blending

a unblended single source data in common gun domain; b blended dual source data in common gun domain; c unblended single source data in common receiving point domain; d blended dual source data in common receiving point domain

Figure 5 shows the separation results of DeamNet, DnCNN, and U-Net networks for actual blended acquisition data in the common-shot domain. From Figure 5, we can find that all three networks can complete the deblending and separation of the source for actual blended acquisition data. At the same time, compared to DnCNN and U-Net, DeamNet still manages to retain more effective signals. This indicates that DeamNet is better suited for practical seismic exploration compared to DnCNN and U-Net and is more in line with the current high-precision seismic exploration requirements.

Table 2 Quantitative evaluation criteria for deblending effect of actual seismic blended mining data based on three different network structures

network name	Minimum Loss	peak signal-to-noise ratio(PSNR/dB)	Training time/s
DnCNN	960.9850	7.6919	590
U-Net	800.8693	8.1912	601
DeamNet	427.0422	8.7471	3012

Table 2 shows the training results of the three networks on the actual data. Like the performance on the synthetic data, the training efficiency of DeamNet is still lower than that of DnCNN and U-Net, but its deblending ability is stronger than that of the latter two.

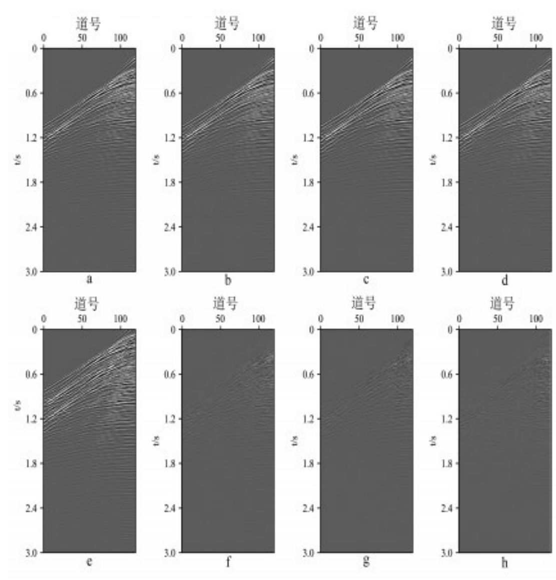

Figure 5 Separation results of common gun domain in actual data

a single source actual seismic data; b single source data separated by DnCNN; c single source data separated by U-Net; d single source data separated by DeamNet; e actual blended mining data; f DnCNN separation results and actual single source error; g U-Net separation results and actual single source error; h DeamNet separation results and actual single source error

4 Conclusion

Multi-source blended mining data has the characteristics of difficult to obtain training data, strong correlation between effective signals, and similarity between different gun line seismic data. The dual-element attention mechanism can take advantage of these characteristics to better complete the blending of blended mining data. While removing aliasing noise, the dual-element attention mechanism helps the DeamNet network to better retain the effective signal, which is conducive to the subsequent processing of separating the single source and improving the imaging accuracy.

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