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Dealiased Seismic Data Interpolation Using Time Dynamic Warping with Dictionary Learning

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Abstract. In seismic data, interpolating regularly missing traces is generally regarded as more challenging than interpolating irregularly missing traces. To address regularly missing cases, an anti-aliasing strategy should be incorporated. In this paper, we employed dictionary learning approaches for seismic data anti-aliasing interpolation. In dictionary learning, it is crucial to pre-interpolate the sampled data to ensure that the learning dictionary captures the data structure. Currently, the nearest trace interpolation method is being used for pre-interpolation, which fails to utilize the spatial characteristics of data events. To overcome this limitation, we propose a pre-interpolation dictionary learning method based on time dynamic warping. The time dynamic warping technique calculates the similarity between two adjacent sampling traces and establishes the most similar path between the points. Subsequently, pre-interpolation data is obtained by linearly interpolating between these similar points. In the experimental comparison, we evaluate the performance of our proposed approach against the nearest pre-interpolation dictionary learning method. Synthetic and field date both demonstrate superior performance when using our proposed approach compared to the nearest pre-interpolation dictionary learning method.

AMS subject classifications: 68T05, 97N50

Key words: Seismic data interpolation, Dynamic time warping (DTW), Dictionary learning. †

1 Introduction

Due to economic limitations or environmental constraints, incomplete traces in obtained seismic data, whether irregular or regular along the spatial coordinates, are inevitable. This has a significant impact on seismic inversion, amplitude versus angle analysis, and migration. Therefore, interpolation plays a fundamental role in addressing this issue [1].

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Most state-of-the-art seismic interpolation algorithms, such as sparse transform, deep learning, and dictionary learning, have gained popularity in the past decade. Sparse transform methods, including wavelet [9], curvelet [10], and shearlet [1], enable sparse representation of seismic data in a transform domain. In the interpolation method proposed by Yang et al. [10], the integration of the curvelet transform into the projection onto convex sets(POCS) method aims to extract localized features from seismic data. Gan at al. [1] utilized the seislet transform to interpolate regularly missing traces in seismic data. However, sparse transform interpolation methods rely on the sparsity assumption and require different parameter selections for different datasets, resulting in poor flexibility. Recently, deep learning has emerged as a new algorithm that can automatically learn features and relationships hidden in large datasets. Wang at al. [8] applied advanced deep learning methods to perform anti-aliasing interpolation on seismic data, allowing for the extraction of complex features from the training data in a non-linear fashion using self-learning techniques. This methodology can effectively address the limitations posed by the linear assumptions, sparsity, and low-rank constraints that are commonly associated with traditional interpolation techniques. Saad et al. [7] proposed an unsupervised deep learning framework for simultaneous denoising and reconstruction of 3D seismic data, without the need for prior information or labels. Zhang et al. [13] designed an interpolation technique for seismic data utilizing denoising convolutional neural networks (CNNs). However, network construction in such methods relies on labeled data and faces challenges of overfitting. Dictionary learning (DL) is another adaptive learning method that does not require labeled data. Various types of dictionary learning have been proposed, such as K-means singular value decomposition (K-SVD) [6], data-driven tight frame (DDTF) [11], tree structure dictionary learning [2] and double learning method [4]. In these DL methods, K-SVD is one of the most effective overcomplete learning algorithms. The basic idea is to represent the dictionary as a matrix, where each column is represented by an atom (a basis in the dictionary). The algorithm optimizes the results by alternating the process of updating the dictionary and sparse representation. In each iteration, the atoms in the dictionary and the sparse representation of the data are continuously updated by minimizing the residual between the data and its sparse representation while maintaining the sparsity of the dictionary [3]. Since one SVD decomposition only updates one column in the dictionary, multiple SVD decompositions need to be performed in each iteration, resulting in a large amount of calculation. Based on this situation, the DDTF method [11] is proposed. This method only needs to update the dictionary through one SVD operation in each iteration, which significantly reduces computational requirements and enhances efficiency in calculations.

In DDTF method, the dictionary is learned from the sampled data. However, since the sampled data contain missing traces, the DL method cannot capture the data structure effectively. Therefore, pre-interpolation is essential before dictionary learning to restore the missing traces. The nearest trace interpolation (NNI) method was used by [2] and [11]. NNI simply utilizes the nearest trace to estimate the missing trace, without considering the underlying data structure. Consequently, the resulting dictionary lacks the neces-