

P-wave Velocity Estimation Using Few-shot Learning Constrained by Seismic Images and Well-logging Data

Introduction

Subsea permafrost is a frozen sedimentary layer distributed beneath the seafloor in high-latitude continental shelf environments (Pullan et al., 1987; Buddo et al., 2022). Because frozen and unfrozen sediments have different seismic velocities, accurate velocity estimation is essential for reliable seismic imaging, identification of subsea permafrost, and interpretation of subsurface structures (Pullan et al., 1987; Johansen et al., 2003). Seismic velocity estimation is commonly used by seismic imaging methods and well-log analysis (Yilmaz, 2001; Virieux and Operto, 2009). Seismic imaging can provide continuous information on broad subsurface velocity structures over the survey area. However, seismic imaging in Arctic Sea environments is challenging because of contrasts with strong velocity, complex shallow geology, and limited quality of field seismic data (Ramachandran et al., 2011; Kang et al., 2021). In contrast, well-log data provide reliable P-wave velocity information, but they are usually available only at a few borehole locations (Hu et al., 2013). This makes it difficult to build detailed velocity models and interpret permafrost boundaries (Hinz et al., 1998; Kang et al., 2021).

Recent machine learning methods have been used to improve seismic velocity estimation by learning the relationship between seismic images and subsurface velocity structures (Yang and Ma, 2019; Bustamante et al., 2024). However, most supervised learning methods require many labeled velocity models for training (Chen et al., 2022). This is difficult in Arctic seismic surveys, where well-logging data are limited and unevenly distributed (Hu et al., 2013; Bustamante et al., 2024). To address this problem, a learning method that can work with limited well-log velocity profiles is needed (Fei-Fei et al., 2006; Chen et al., 2022; Lee et al., 2024).

In this study, few-shot learning is used to train the network with a small number of well-logging data and to support velocity model building for seismic imaging. The proposed method incorporates multiple well-logging data as labels to improve the geological consistency of the predicted velocity model. Reverse time migration (RTM) images and background velocity are used as input features, allowing the network to learn structural patterns associated with permafrost boundaries while being constrained by measured borehole velocities. The few-shot learning network is based on a U-Net encoder-decoder architecture and predicts velocity profiles. After training at well locations, the network is applied to the entire survey area to estimate a continuous velocity model.

Training strategies

The proposed few shot learning strategy uses a small number of well-log velocity profiles as labels for velocity model estimation. The background velocity model and the RTM image are used as input data, while the corresponding P-wave velocity profiles at selected well locations are used as label data. This input configuration allows the network to learn both smooth velocity trends and structural features related to subsurface reflectors. The network is based on an encoder-decoder architecture designed to extract seismic image features and predict P-wave velocity (Figure 1). After training, the trained network is applied to the full model domain to estimate a laterally continuous velocity model. This strategy aims to improve prediction stability while maintaining the advantage of learning from limited well-logging data.

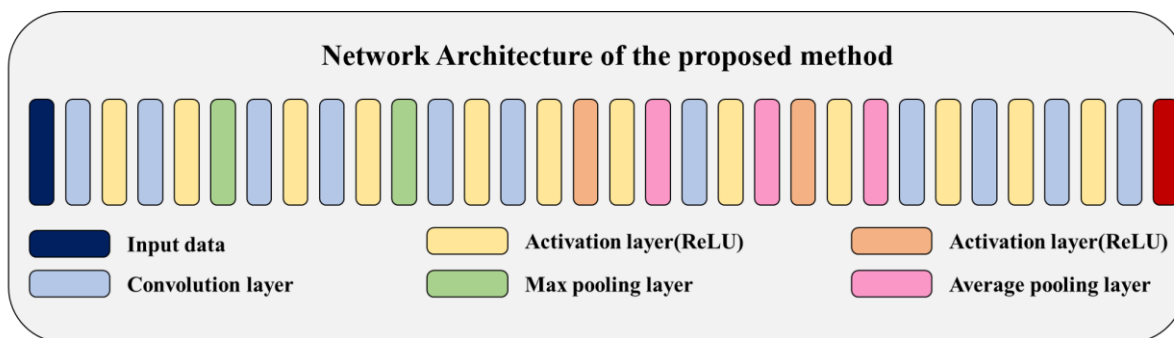


Figure 1 The proposed network architecture for prediction of well-logging data.

For the numerical example, a synthetic P-wave velocity model was constructed based on reported characteristics of Arctic subsea permafrost. Johansen et al. (2003) showed that ice-bonded and partially ice-bonded sediments beneath the seafloor can have P-wave velocities of approximately 3,500 m/s and 2,800 m/s, respectively. In addition, high-velocity structures have been observed at depths of about 100–650 m in shallow shelf areas, where water depths are generally less than 50 m (Johansen et al., 2003; Kang et al., 2021). Based on these observations, we constructed a synthetic velocity model that includes a shallow high-velocity layer, a transition zone, and background sediments (Figure 2).

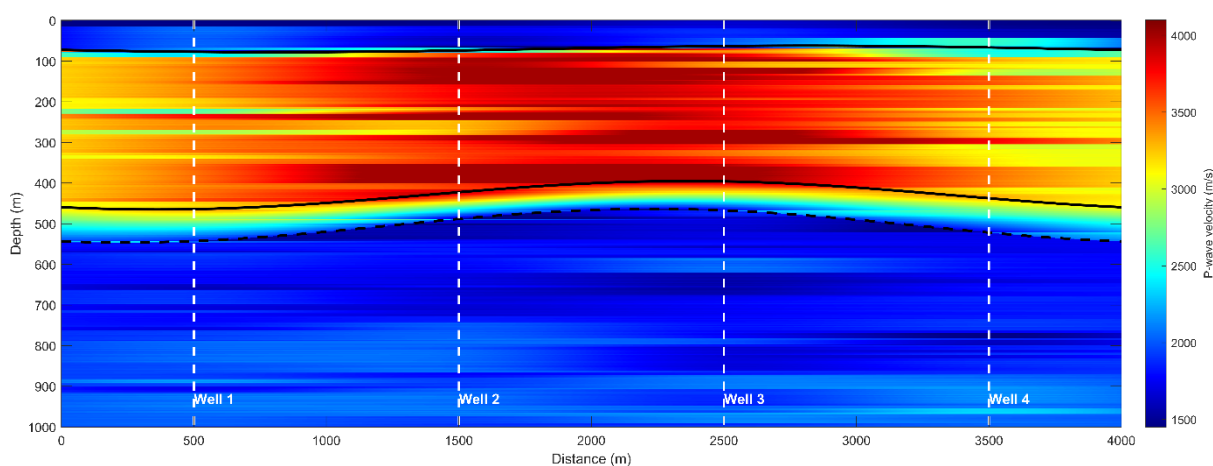


Figure 2 True velocity models for a numerical example. White dashed lines indicate the positions of the well logs. The solid and dashed black lines represent the base of the permafrost zone and the lower boundary of the transition zone, respectively.

Numerical examples

In this numerical example, we selected synthetic well-logging datasets with similar velocity trends as labels for training. This selection was intended to reduce label inconsistency and improve the stability of the predicted velocity model. The background velocity model used as network input was generated by smoothing the synthetic true velocity model. For RTM image generation, synthetic seismic data were modeled using a marine streamer acquisition geometry consisting of 120 hydrophone channels and 79 shots. The synthetic P-wave velocity model has a size of 4,000 m $\times$ 1,000 m and was discretized with a 1 m grid interval. Wave propagation modeling was performed using a source wavelet estimated from Arctic seismic data. The maximum frequency of the source wavelet was limited to 150 Hz. The recording time and temporal sampling interval were set to 1.0 s and 0.1 ms, respectively. The modeled shot gathers were then migrated by RTM using the smoothed background velocity model as the migration velocity, and the resulting RTM image was used as an input feature for the network. After training, the proposed network was applied to the entire model domain to predict a continuous P-wave

velocity model. Figure 3 shows the predicted velocity model and reverse time migration result. The result preserves the main velocity structure, including the shallow high-velocity layer and the transition zone around 450–550 m depth. The predicted model also shows continuity across the model, indicating that well-log constraints can be extended to regions.

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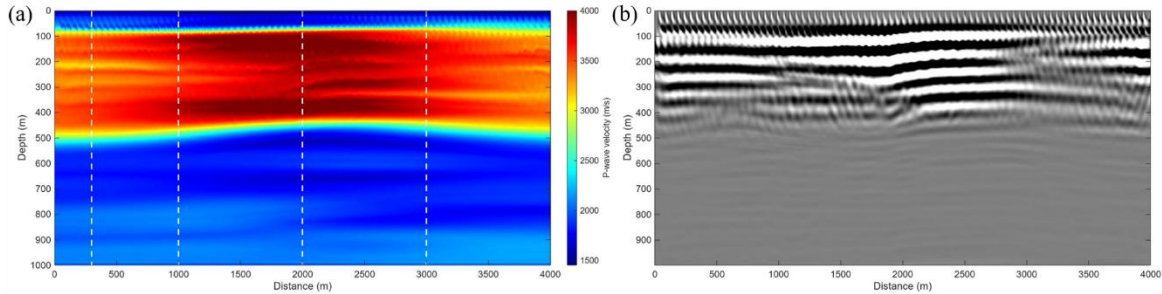


Figure 3 (a) Predicted velocity model, and (b) reverse time migration result. The white dashed lines show the locations of four well logs used for test data.

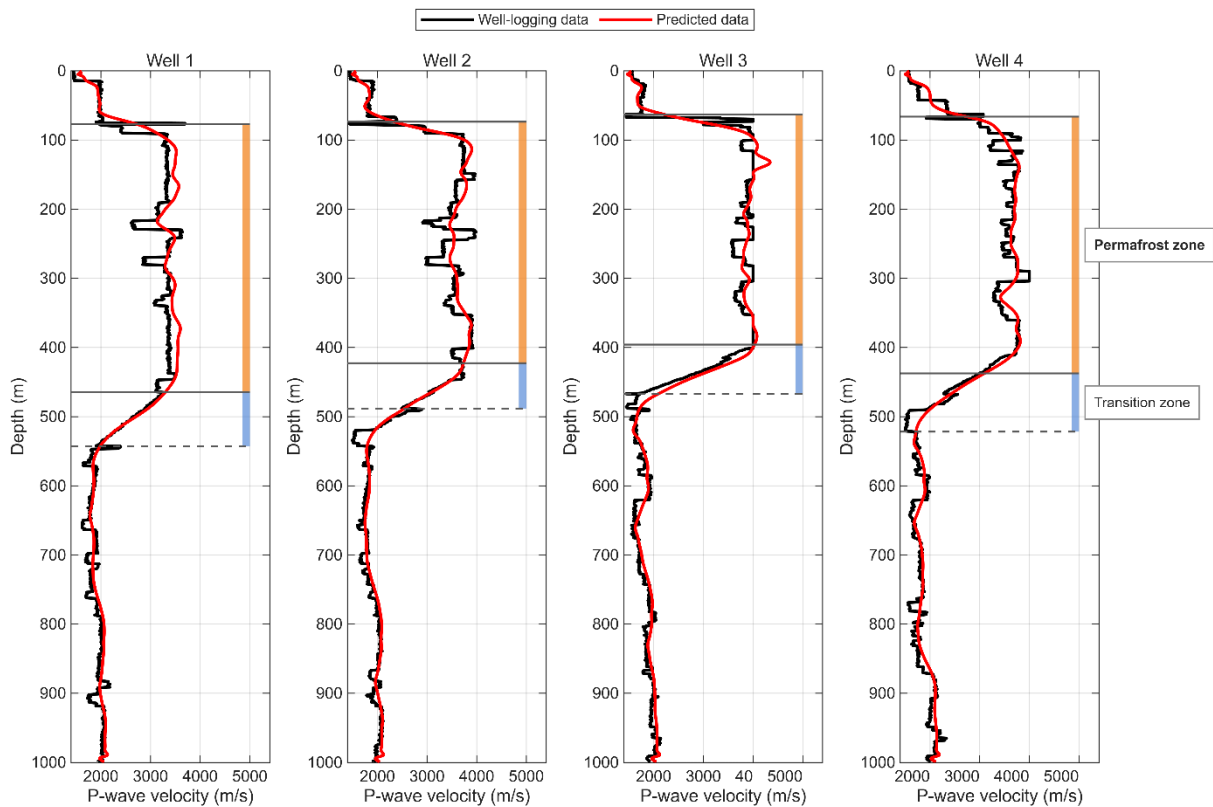


Figure 4 Comparison of vertical velocity profiles at four well locations ($x = 300$ m, 1,000, 2,000, and 3,000 m).

Figure 4 compares the reference and predicted P-wave velocity profiles at four well locations of 300, 1,000, 2,000, and 3,000 m. The predicted profiles generally reproduce the main velocity variations observed in reference data. In particular, the shallow high-velocity interval and the velocity decrease across the transition zone are captured. This comparison indicates that the proposed few-shot learning method can estimate not only the overall velocity trend but also the depth range of permafrost-related velocity boundaries.

Conclusions

The proposed few-shot learning approach estimated a continuous P-wave velocity model using limited well-logging data. The predicted velocity model preserved the permafrost zone and transition boundary associated with Arctic subsea permafrost structures. The comparison with test well profiles showed that the method can capture both overall velocity trends and boundary depths. However, it is suggested that fine-scale velocity variations within the permafrost were not fully predicted due to the resolution limitations of the RTM input data. This indicates that few-shot learning is effective for capturing velocity trends and boundaries, but higher-resolution seismic inputs or additional well-log constraints are needed to recover detailed internal structures.

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