Automated Seismic Velocity Picking via Deep Semantic Segmentation

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ABSTRACT

We developed a deep neural network model to automatically implement velocity analysis from semblance images, eliminating the need for extensive manual picking. Our method treats velocity picking as an image segmentation task on input semblance images. We train a U-Net convolutional neural network architecture using over 2000 common depth point (CDP) gathers and corresponding picked velocity profiles to segment the semblance images into distinct velocity regions. We optimize the model using techniques like sequence learning and customized loss functions. When evaluated on test CDP gathers excluded from training, the model achieved 99.3% accuracy in delineating the major velocity boundaries. This demonstrates the capability for high-quality automated velocity picking directly from seismic images using deep learning.

Keywords: Velocity analysis, Deep Learning, U-Net, Encoder-Decoder

INTRODUCTION

Velocity analysis is critical for accurate seismic imaging and subsurface characterization. However, conventional workflows rely heavily on tedious, subjective manual picking of velocity surfaces on semblance gathers (Yilmaz, 2001). Automating velocity analysis could greatly increase productivity. Recent advances in deep learning have driven adoption in many seismic applications, including processing and interpretation tasks (Yu and Ma, 2021). However, few published studies explore harnessing deep learning specifically for automating core seismic processing tasks like velocity analysis (Yang and Ma 2019).

In this work, we demonstrate automated velocity prediction by formulating this challenge as an image segmentation problem on input semblance images. We customize a U-Net convolutional neural network (CNN) architecture to delineate major velocity boundaries in the semblance.

The encoder-decoder structure enables contextual feature extraction while the lateral connections combine multi-scale information for precise velocity localization (Jégou et al., 2017). We optimized the network training using custom loss functions with added regularization and velocity matching to improve convergence and accuracy.

When evaluated on unseen land surveys, the method achieves over 99% pixel-wise accuracy in predicting velocity labels from the input semblance images.

Methods

We formulate velocity prediction from semblance images as a pixel-wise semantic segmentation task. This model is based on the U-Net CNN architecture which follows an encoder-decoder structure (Ronneberger et al, 2015). The encoder progressively compresses the input image into lower resolution feature representations, capturing useful contextual information. The decoder then upsamples these features into a full-resolution segmentation map, enabling precise localization of velocity boundaries.

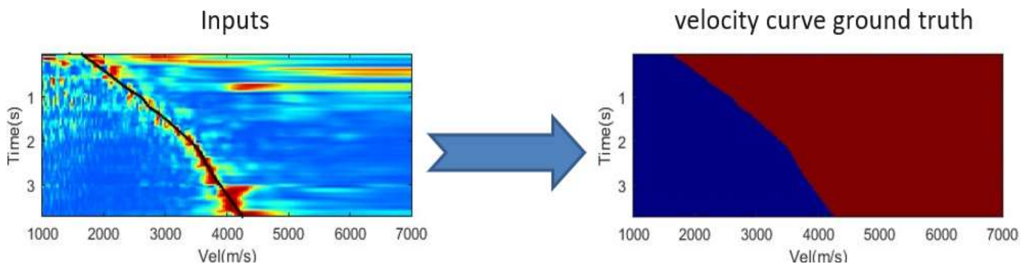

Figure 1. Formulation a semantic segmentation task. Input semblance with velocity picks (left) and output categorical velocity mask (right).

We recast velocity picking as image segmentation (Figure 1), therefore, the model predicts velocity regions directly from input semblance.

Training Strategies

Various strategies were explored to enhance model accuracy:

- **Network Architecture:** We experimented different U-Net depths, including 3 and 4-level encoders, varying filter and Kernel sizes to balance feature learning capacity and overfitting risk.

- **Input Configuration:** We tested single semblance images vs sequences of depth frames. Sequence inputs better encode velocity consistency but require more data to prevent overfitting.

- **Loss Functions:** We designed custom hybrid loss terms, combining pixel-wise cross entropy (CE(p(x;θ),y)) with regularization penalties like Tikhonov smoothing ($\alpha \, \|L\, v\|_2^2$) and velocity matching ($\lambda \, \|v_{Pred}(x;\theta) - v_{True}(x)\|_2^2$) metrics.

Smooths velocity predictions to prevent unrealistic fluctuations:

$$\mathrm{L}(\theta) \; = \; CE\ (p(x;\theta),\mathrm{y}) + \alpha \, \|L\, v\|_2^2 \qquad (1)$$

Here, α is a hyperparameter controlling the regularization strength. The regularization term penalizes first-order differences between predicted velocities, promoting smoother trends.

- **Velocity Matching Loss:** Incorporates regularization for agreement between predicted and true velocity trends:

$$\mathrm{L}(\theta) \; = \; CE\ (p(x;\theta),\mathrm{y}) + \lambda \, \|v_{Pred}(x;\theta) - v_{True}(x)\|_2^2 \qquad (2)$$

Here, λ is a hyperparameter controlling the strength of the regularization term. The regularization term focuses on overall patterns, reducing sensitivity to local variations. Fine-tuning the coefficients (α and λ) significantly improved training stability. The final U-Net configuration is depicted in Figure 2. key hyperparameters summarized in Table 1.

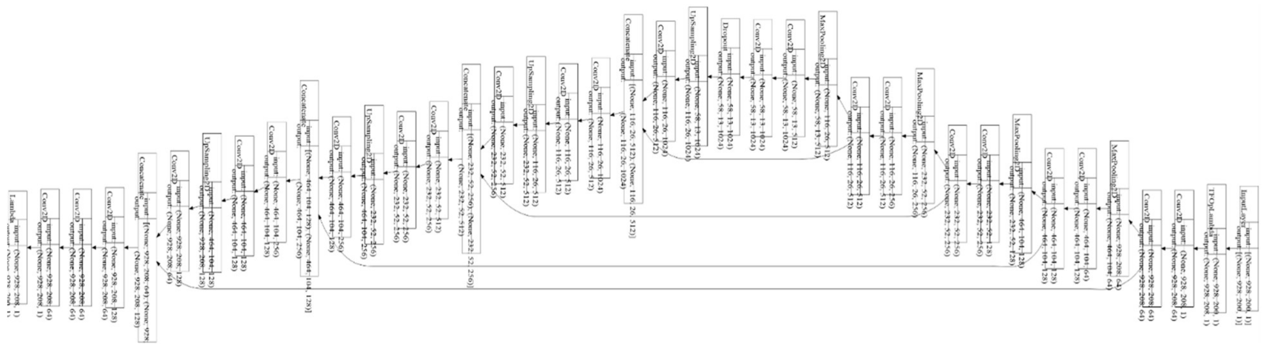

Figure 2. **The final optimized U-Net architecture used for velocity prediction.**

Table1. The optimized U-net model Key hyperparameters.

Network	Depth	Variables	Mini Batch	Loss	Validation data	Validation Accuracy	Epochs
U-Net	3	20.1 M	16	$CE\ (p(x;\theta),\mathrm{y}) + \alpha \, \|L\, v\|_2^2$ $+\lambda \, \|v_{Pred}(x;\theta) - v_{True}(x)\|_2^2$	10%	99.3	12

The network trained on a dataset of over 2000 CDP gathers, with 80% for training, 10% for validation, and 10% as an unseen test set. Model parameters were optimized by minimizing a hybrid cross-entropy segmentation loss along with custom regularization penalties.

Training Analysis

To analyze model performance, we visualized predictions on sample training CDPs (Figure 3(a)). Strong agreement between predicted and true velocities was observed, with velocity differences <50 m/s. We also assessed lateral consistency on full velocity sections (Figure 3(b)). The predicted trends match major patterns of true sections. Velocity differences are small, highlighting accurate predictions.

Test Analysis

To evaluate generalizability, we analyzed model predictions on unseen test CDP gathers (Figure 4). The predicted velocity profiles show strong agreement with the true manually picked velocities. This demonstrates the model can accurately estimate velocities even for new seismic lines excluded from the training data. When aggregated over multiple adjacent CDP gathers, the predicted sections match the major patterns and trends of the true velocity surfaces. Minor smoothing of some local variations is observed, but key boundaries are delineated. By effectively learning robust velocity relationships from the training data, the network translates well to unseen CDP gathers.

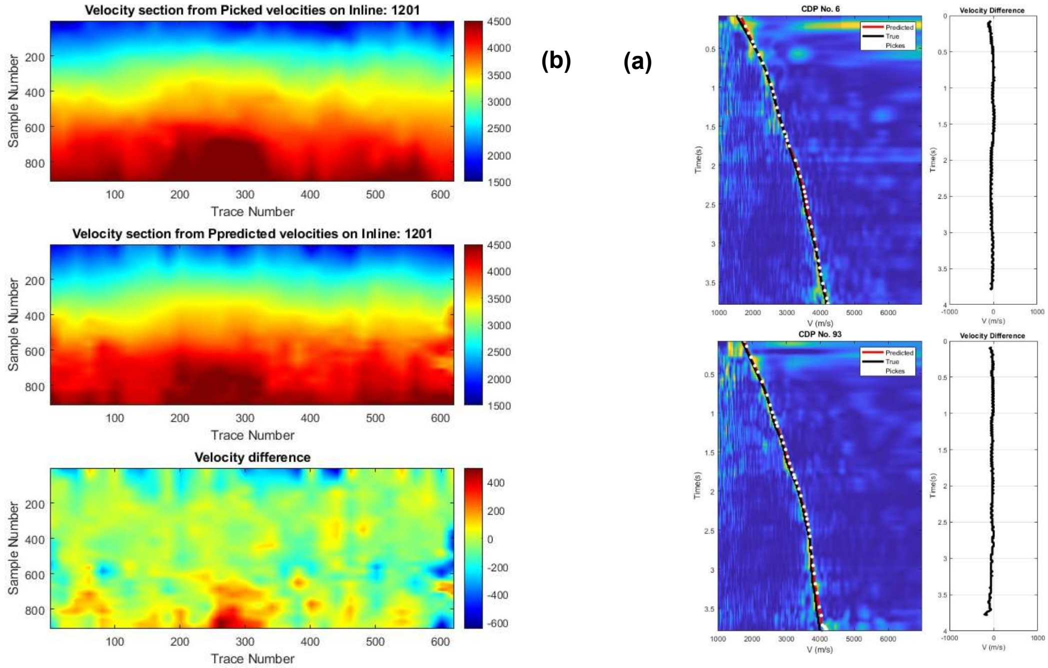

Figure 3. a) Left: Predicted velocity (red), true manually picked velocity (Black), Right: velocity difference for sample CDP gathers from the training dataset., b) Full velocity section of model prediction on training CDP gathers of line 1201. Top: True manually picked velocities. Middle: Predicted velocities. Bottom: Difference.

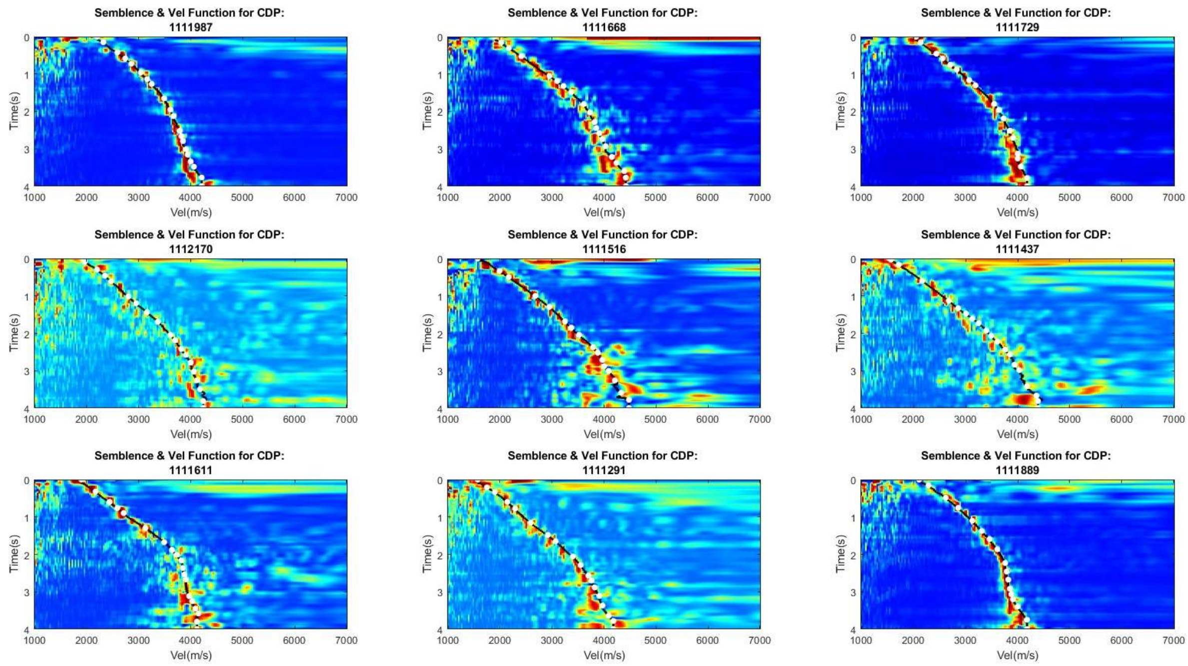

Figure 4. The predicted velocity profiles on semblance gathers for 9 representative CDP sections. This seismic line and its CDP gathers were intentionally excluded from the training dataset to assess the model's ability to generalize to unseen seismic data.

The uncertainty map in Figure 5 provides useful insights into regions where the velocity predictions may require additional QC. The uncertainty stems from areas with ambiguous seismic signatures where the model has lower confidence. Focusing manual QC efforts on these high uncertainty zones could enable efficient quality control.

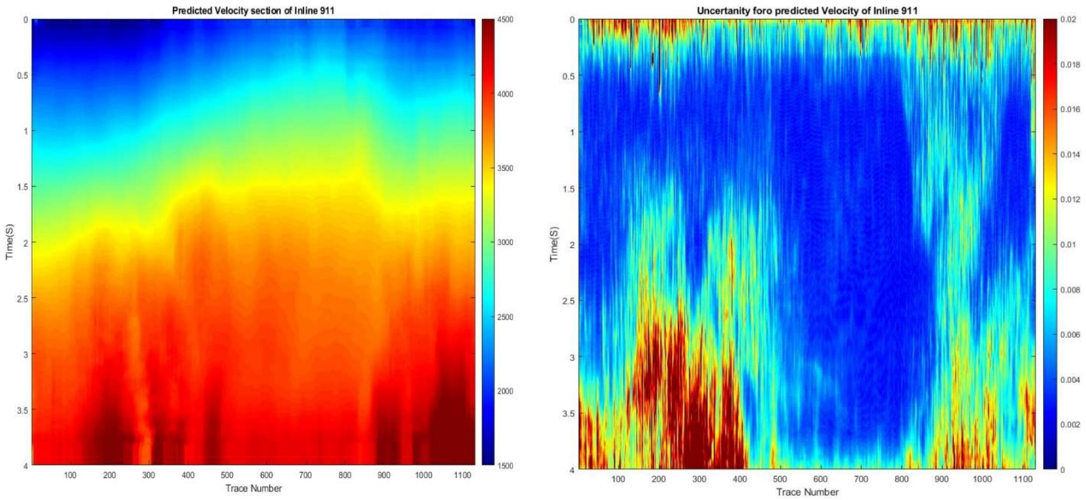

Figure 5. ***Left: Full velocity sections of model predictions on test CDP gathers (Test Line). Right: Uncertainty map for velocity predictions on the test seismic line. Warmer colors indicate higher uncertainty in the predicted velocities.***

CONCLUSION(S)

In this work, we presented a customized deep learning model for fully automating velocity picking from seismic data. By recasting the velocity picking problem as an image segmentation problem on semblance gathers, we can leverage CNN architectures to accurately classify pixels into distinct velocity regions with only light QC needs. Our model achieves real-time velocity prediction per CDP gather. The proposed DL workflow has the potential to greatly increase productivity for velocity model building in seismic processing.

In comparison with the traditional manual velocity picking, this method provides a dense picking of velocity in temporal and spatial direction leading to more accurate and resolvable velocity, this method also needs much less time as it leverages high performance GPU computing. For the QC purpose, however, we need a finite number of control points, so we can extract knee points of the predicted trend which with an uncertainty map extracted from the DNN model serve the requirements for quality control and manual correction purpose. This method also serves as a demonstration case study for injecting deep learning approaches to augment traditional geophysical techniques.

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