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Convolutional Neural Network based Geophysical Model for Automatic Velocity Picking in Seismic Data

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Summary

Velocity analysis is a time-consuming task which is mostly performed manually. We develop a novel data-driven ensembled learning strategy for combining geophysical models with Convolutional Neural Network (CNN), which uses spatiotemporally varying image data for training and predicting purposes. We perform extensive experiments using nine field datasets and evidence better performance compared to current state-of-the-art method. The results show near expert prediction using over 3000 semblances collected from different fields.

Introduction

To address the problem of automatic velocity picking, there has been a recent push to use significantly improved abilities1 of deep neural network or deep learning. For example, studies of using Recurrent Neural Networks (RNN)2 and long short-term memory (LSTM)3 have been carried out to address this problem. However, given that the nature of this problem needs expert attention and image processing on one hand, and the superiority of the convolutional neural network (CNN) in extracting features from images on the other hand, the state-of-the-art velocity picking methods are based on CNN4,5 . Ferreira et al.4 applies an initial velocity picking on semblance and then refines it using CNN. The proposed CNN, however, needs both gather image and semblance image along with the true velocities for training. Besides that, Ferreira et al. use only one of the existing CNN architectures without having any comparison with other CNN architectures.

Our work is most closely related to the work of Park and Sacchi5. However, their method only focuses on the results of the CNN without considering the existing geophysical knowledge about the problem. In contrast, the geophysical knowledge is one of the main steps in our hybrid method where it is used to refine the CNN prediction results. Furthermore, their work outputs regions of velocities as a number in range 2000m/s and 4000m/s, whereas our proposed method has the coverage on a wider range of velocities (from 1500m/s to 6000m/s) that includes most of the real-world rock velocities.

Method and Workflow

The objective of the algorithm is to get a semblance panel input image S and automatically determine stacking velocities V_Γ (henceforth "velocities") on that semblance where travel-time set Γ is detected in the reference file. For this purpose, in this section, we explain our hybrid CNN approach combined with geophysical models. The main process of our method is shown in Figure 1.

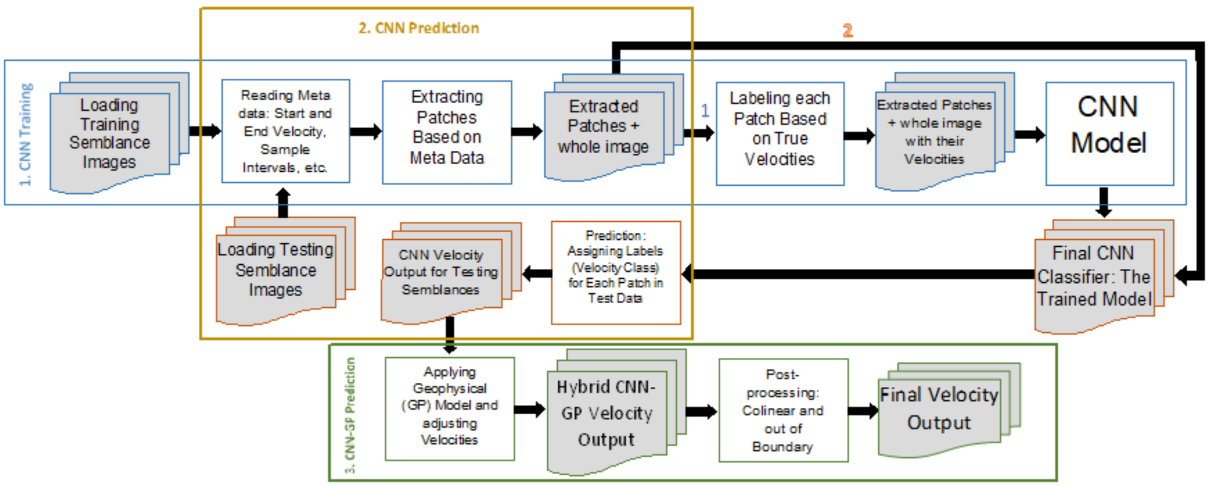

Figure 1: Overview of our approach which includes three phases: 1. CNN Training 2. CNN Prediction 3. CNN-GP Prediction.

The main three steps of the approach are 1) CNN Training 2) CNN Prediction 3) CNN-GP Prediction. To do this, first "Semblance Encoding" is implemented in both steps one and two. The reason is that, in the real world, the traveltime of the picked velocities are selected by an expert. Therefore, in the absence of the traveltime in CNN prediction phase, our semblance encoding objective is to extract patches from input image that can simulate the travel-time selected by the expert. Next, the labelling of the velocities to fit into our classification workflow process while keeping its value precisely is an important step. Based on expert suggestion, we expect velocities picked for the semblances to fall within a certain range of rock velocities obtained from decades of observational and empirical evidence (between 1500m/s and 6000m/s). In the classification problem, the velocity range in each class is considered to be 25m/s for a total of 180 classes (labels).

After training and testing is done with CNN, the hybrid geophysical step is designed to provide quality control on initial velocities predicted by CNN. To perform quality control and assess the validity of the velocities predicted by CNN, we employed the Dix equation6. The interval velocities are approximated by applying Dix equation on the predicted stacking velocities, and if out of range, they are replaced with the next best prediction.

Results and Conclusions

A summary of computational results is presented in Table 1. Performance of the proposed method versus Park's and Sacchi's method5 is evaluated in terms of (1) Velocity Picking Distance to Reference (VPDR) where performance is measured by the average velocity displacement between the true velocity and predicted velocity to evaluate the regression prediction ability of the methods, (2) Mean Square Error and Mean Absolute Error in which I quantify the classification performance for our ordinal multi-class problem, and (3) the training and testing run time. The reported run time does not include patch extraction time for either method.

Table 1: Results on our method and state-of-the-art method (Park&Sacchi) using two separate field datasets for test.

Dataset	Method	VPDR	MSE	MAE	Time (s)
D1	Ours	280.89	233.2	11.2	630
	Park&Sacchi	457.15	835.82	18.26	2815
D2	Ours	400.76	455.68	16.01	923
	Park&Sacchi	548.125	977.55	21.9	2810

As can be seen in Table 1, our method consistently out-performs the state-of-the-art method5 on both field datasets with the margin of at least 23% for all performance metrics.

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