**Main Idea**

in this paper, we propose a method that requires only a small dataset to train an encoder-decoder CNN based on the U-Net architecture for seismic fault detection. The U-Net architecture was originally designed for biomedical segmentation tasks such as cell segmentation.

Here, we treat seismic fault detection as a semantic segmentation task, i.e. we can classify each point in a seismic section into one of two classes, namely, faults and non-faults.

obtaining the most accurate result is not the intention of this paper. Instead, we mainly focus on the possibility of using a small training set to train neural networks for seismic fault detection.

**Problem**

Because faults may indicate the locations of petroleum reservoirs, seismic fault detection is an important task in seismic interpretation. However, traditional methods require interpreters to trace and pick faults manually. This process consumes substantial amounts of manual work and time; as a result, the interpretation efficiency is very low.

**Summery**

training a large number of network parameters requires a large number of samples; thousands or even millions. For common researchers and interpreters in geophysics, a very large amount of manually labeled real data is usually beyond reach. Therefore, in work involving seismic fault detection using deep learning, researchers always use generated synthetic data rather than real data as training sets, in this paper, we propose a method that requires only a small dataset to train an encoder-decoder CNN based on the U-Net architecture for seismic fault detection. Therefore, we can use real data as the training set without any concerns about insufficient data.

One typical application of the CNN is for classification tasks, where the output of each image is a one-hot vector indicating the likelihood that the image belongs to each class. However, in some tasks, such as cell segmentation in biomedicine, we need to classify not only an image but also each pixel in the image. This kind of task is called semantic segmentation (or image segmentation).

Many studies have shown that U-Net performs well not only on biomedical segmentation but also on many kinds of semantic segmentation tasks.

The training part has two steps: preprocessing and CNN model training. In this part, we choose N seismic sections with obvious faults from raw inputs as the training set of the CNN.

The proposed method is practical, especially for researchers and interpreters who have difficulty obtaining a large amount of labeled real data. Furthermore, the method has two obvious advantages. One is its high cost-effectiveness, that is, several labeled sections can train a network that can make accurate predictions; another advantage is that it can allow us to use real data as the training set without any concerns about insufficient data.

**Dataset**

In one of the experiments, we randomly generated 140 images with dimensions of 256 × 256 from seven [real] raw input seismic sections with dimensions of 451 × 1001 during the preprocessing and generated 140 corresponding labels with dimensions of 256 × 256. The CNN model we used was a U-Net with four pooling layers, as shown in figure 2. We used an Adam Optimizer (Kingma & Ba 2014) and trained the network for 100 epochs with a learning rate of 1e-4. Each epoch was trained on batches, and each batch contained 10 images. The training time of the CNN model was approximately 30 minutes.

The FDA index reflecting the result accuracy at the manually labeled positions was 0.655, and the IoU(Intersection over Union) value was 0.500. The IoU value was lower than the FDA index value because the CNN may detect small faults that have not been manually labeled.

Chart

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