Karst cave detection using physical model dataset and deep learning

Introduction

On seismic migration sections, anomalous bright spots, called the string of beads response (SBR), are common features of carbonate karst reservoirs at the seismic scale in the Tarim Basin, China. Karst caves can be used as indicators of high-quality oil and gas reservoirs, and have been the main drilling target for exploration and development in the Tarim Basin.

Previous researchers (Zeng et al., 2011) indicated that the reflection characteristics of bright spots on seismic profiles of carbonate karst caves in Tarim Basin, China, and pointed out that the geological forms corresponding to the bright spots with strong amplitude of SBRs include underground rivers, sinkholes and tower-shaped caves. Yang et al. (2012) analysed the formation mechanism and structure of carbonate reservoir, and the influence of karst cave dissolution degree on waveform and reflection amplitude. Halpert et al. (2014) based on the different attribute characteristics of karst caves, according to the different functions of seismic attributes in geological body segmentation, multi-seismic attributes are fused and segmented. Xu et al. (2016) established a variety of physical models to simulate the shape of karst caves through fillers such as rubber and resin, and studied the influence of different shapes, sizes, fillings and spatial distribution on the reflection characteristics of karst caves by using modeling and migration methods.

Compared with previous studies on geological bodies such as fault and salt bodies, karst caves in Tarim Basin are more complex, and the reflection characteristics of seismic records have not been fully studied. The results obtained by numerical forward simulation are different from the actual situation, and it is difficult to obtain the true shape of karst caves through actual seismic data.

We regard cave detection as a 3D image segmentation problem. By combining two physical models with seismic attributes, 520 pairs of datasets are made which contain caves with different shapes, scales, porosities and seismic wave propagation velocities. Our CNN shows powerful performance in the validation dataset of karst caves with different spatial positions.

Physical model dataset

We adopt two karst cave physical model datasets, and the physical models are made according to the scale of 1: 20000, with 1mm corresponding to the actual situation of 20m. In the design of observation system, the horizontal and vertical bins correspond to the actual situation of 25m, and the sampling rate is 2ms, which is like the actual seismic data acquisition. Model 1 (Xu et al., 2016) is a complex actual karst cave model, and the karst cave are divided into 18 zones as shown in Figure 1a. Selecting the area of 640 (inline) × 785 (cross line) × 301 (time) as the dataset. The shape, size and corresponding velocity of the physical model cave are known. If the position of karst cave central point in the physical model in space is obtained, the labels can be marked. RMS amplitude with a time window of 200ms is selected to assist in calculating the cave location. By comparing the physical model slice (figure 1a) and RMS amplitude time slice (figure 1b), RMS amplitude can well represent the cave location information. We choose the point where the maximum rms amplitude in a square area as the cave center point. Finally, the label of karst cave in the whole area is shown in figure 1c. Model 2 is a relatively single physical model. There are 32 cylindrical karst caves with the same seismic wave propagation speed and different diameters and heights. The shape and distribution of caves are shown in figure 1d.

Next, we use data augmentation to expand the data volume. The way for data augmentation is like introduce folds into synthetic seismic records by Wu et al. (2019):

\[ f(x, y) = \sum_{k=1}^{N} b_k e^{-\frac{(x-c_k)^2 + (y-d_k)^2}{2\sigma_k^2}} \] (1)
It is a Gaussian function characterized by many parameters, in which the parameters $b_k, c_k, d_k$ and $\sigma_k$ are randomly selected within a certain range. After adding folds, the values on the previous dataset $s(x, y, z)$ become $s_k(x, y, z + f(x, y))$. By adding folds, the relative positions of different caves can be changed without basically affecting the waveform characteristics of caves, which greatly improves the diversity and quantity of datasets.

Figure 1 (a) Top-down view of the cave distribution of Model 1 (Xu et al., 2016), (b) Time slice at 200ms RMS amplitude of the Model 1, (c) 3D karst cave dataset of the Model 1 and (d) 3D karst cave dataset of the Model 2.
Because the datasets of Model 1 and Model 2 are too large and irregular in scale, and the neural network has certain requirements on the input size, the size of each dimension should be divisible by $2^n$, where $n$ is the maximum number of pools used by the neural network. The network mentioned later uses the maximum pooling layer for 5 times, so the size of dataset should be a multiple of 32. We choose the commonly used data size of 128×128×128, and each 3D data is randomly selected from a large dataset, which can greatly improve the diversity of data.

Finally, we made 360 pairs of datasets of Model 1 and 80 pairs of datasets of Model 2 as training datasets, and 40 pairs of datasets of Model 1 and 40 pairs of datasets of Model 2 as validation datasets.

**CNN architecture and model training**

We use the CNN named ResU-Net (Res-50) as shown in figure 2, which is based on U-Net and added Res-50 residual module. Res-50 can increase and decrease the number of feature image channels by 1×1×1 convolution kernel, which can greatly reduce the amount of computation while ensuring the ability of feature learning. Therefore, we constructed a deep neural network with 45 convolution layers, and the number of feature image channels increased from 16 to 512 in multiples of 2.

The amplitude values of different real seismic data can be a big difference, we normalize all the datasets, and the standard deviation of each data is subtracted from its average value. To increase the diversity of data and improve the generalization ability of the training model, the dataset is rotated 90°, 180° and 270° along the vertical axis. The model has been trained for a total of 30 epochs, the accuracy reached 99%, and the loss decreased to 0.002 in validation datasets.

![Figure 2 CNN with the architecture of a U-Net and Res-50 residual module.](image)

**Results**

Due to the temporary lack of actual data of karst cave reservoirs in Tarim Basin, China. The generalization ability of the model is tested on the untrained validation datasets. The profile shown in Figure 3a is the image of square karst cave, Figure 3b is the mark of karst cave in label, and figure 3c is the test result of the model, karst caves in the zone are well detected. Figures 3d is a crossline profile of model 1, the karst caves in this profile are quite complex in shape compared with the karst caves in figure 3a, it can still be well predicted in figure 3e. Through the tests on the validation sets shown that trained model has good performance in generalization, and the karst cave can still be predicted well even when the location of karst cave changes. Finally, as shown in Figure 3, the predicted results are stretched to a certain extent compared with the label. We think that the waveform information of karst caves has some multi-solutions, and the reflection of karst caves of different sizes may be very similar under different seismic wave propagation speeds and porosities. These multi-solutions lead to the model amplifying the predicted karst caves to a certain extent.
Conclusions

We propose a method for producing dataset of karst cave based on physical model and integrating seismic attributes. By this method, the real seismic response characteristics of underground karst caves can be well simulated and accurate labels can be obtained. Through data augmentation, we have greatly expanded the previous small-scale data, changed the relative spatial position of karst caves and greatly improved the quantity and diversity of data. Through training on the physical model dataset and testing on the validation set, the results show that our model can well detect karst caves in different and shapes and spatial positions.

Acknowledgements

This work is sponsored by the National Key R & D Program of China (grant no. 2018YFA0702501) and the Science and Technology Project of CNPC (grant no. 2019A-3310). It is published with the permission of the State Key Laboratory of Petroleum Resources and Prospecting.

References