Deep learning for characterizing paleokarst features in 3D seismic images

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SUMMARY

We propose a supervised deep convolutional neural network (CNN) to automatically and accurately characterize paleokarst features in 3D seismic images. To avoid the time-consuming and subjective manual labelling for training the deep CNN, we propose an efficient workflow to automatically generate numerous 3D training data pairs including synthetic seismic images and the corresponding label images of the paleokarst features. With this workflow, we are able to simulate realistic and diverse geologic structure patterns and paleokarst features in the training datasets from which the CNN can effectively learn to recognize the paleokarst features in field seismic images which are not included in the training datasets. Two field examples in the Fort Worth Basin demonstrate that our CNN-based method is significantly superior to the conventional automatic methods in delineating paleokarst features from seismic images and yielding a clear 3D view of all the paleokarst systems from which the geometric parameters of each paleokarst can be automatically and quantitatively measured.

INTRODUCTION

Buried paleokarst systems, often preserved as collapsed paleocave systems in the stratigraphic record, play important roles in forming worldwide carbonate petroleum reservoirs including those explored in the Fort Worth Basin (e.g., Loucks and Anderson, 1985; Kerans, 1988; Dou et al., 2011), Lower Cretaceous Golden Lane field, eastern Mexico (Viniegra and Castillo-Tejero, 1970; Coogan et al., 1972), Tarim Basin, China (e.g., Maoshan et al., 2011; Desheng et al., 1996; Zeng et al., 2011; Qi et al., 2014), and some other paleokarst-related fields reported in the previous work (e.g., Zhai and Zha, 1982; Andre and Doulcet, 1970; Mazzullo and Mazzullo, 1970; Loucks, 1999). In addition, the paleokarst systems pose potential drilling hazards due to the weakness of the paleokarst zones (Qi et al., 2014; Zhao et al., 2018; Soriano et al., 2019). Therefore, delineating the subsurface paleokarst systems is highly important for petroleum reservoir characterization and production.

In order to facilitate the paleokarst interpretation in 3D seismic images, some seismic attributes including coherence (Bahrhor and Farmer, 1995; Marfurt et al., 1999; Li and Lu, 2014), structural curvature (Roberts, 2001; Al-Dossary and Marfurt, 2006; Di and Gao, 2016), reflector rotation (Marfurt and Rich, 2010), and spectral-decomposition (Qi and Castagna, 2013; Chen, 2016) are calculated to highlight the paleokarst features which provides a clear 3D view of the paleokarst systems in subsurface. CNN-based methods have proven highly powerful to multi-dimensional image processing tasks including image classification (e.g., Krizhevsky et al., 2012; Simonyan and Zisserman, 2014; Szegedy et al., 2015; He et al., 2016), object detection (e.g., Sermanet et al., 2013; Ren et al., 2015; Redmon et al., 2016; Liu et al., 2016; Lin et al., 2017), image segmentation (e.g., Ronneberger et al., 2015; Long et al., 2015; Badrinarayanan et al., 2017; Chen et al., 2017) and so on. Recently, the CNNs have been applied more and more in geoscience problems (Bergen et al., 2019; Bianco et al., 2019) including interpreting geologic features of faults (e.g., Zhao and Mukhopadhyay, 2018; Lu et al., 2018; Wu et al., 2019a,c; Di et al., 2019), horizons (e.g., Geng et al., 2019; Wu et al., 2020, 2019a), salt bodies (e.g., Guilen et al., 2015; Di et al., 2018; Shi et al., 2019; Di and AllRegib, 2020), and channels (Pham et al., 2019) in seismic images.

We consider paleokarst detection in a 3D seismic image as an image segmentation problem and solve it by using a supervised CNN. To train the CNN, we propose a workflow to automatically generate numerous synthetic seismic images, where realistic and various structural patterns and paleokarst features are simulated with some well-defined functions. With this workflow, we automatically generate 100 pairs of 3D synthetic seismic images and the corresponding label images (https://doi.org/10.5281/zenodo.3690252). These 100 pairs of training datasets, with several types of data augmentation, are proven sufficient to train our CNN for paleokarst characterization in 3D seismic images. Although trained by only synthetic seismic images, our CNN shows powerful performance in delineating paleokarst features in field seismic images where the detected paleokarst results are consistent with the previously careful manual interpretation.

SEISMIC SIMULATION OF PALEOKARST COLLAPSES

We propose a workflow (as shown in Figure 1) to automatically generate a lot of 3D synthetic seismic images where the folding and paleokarst-related structure features are diverse and realistic. The paleokarst features are well-defined and therefore can be automatically and 100% accurately labelled out to obtain the target images for training a deep CNN.

Simulate folding structures

In this workflow, we begin with an initial 3D reflectivity model \( r(x, y, z) \) with flat layers (Figure 1a), where the reflectivity values at each layer are randomly generated and are smoothly varying in space. We then randomly generate folding structures (as in Figure 1b) by vertically shearing the flat model and the shearing field is defined as suggested by Wu et al. (2020). By randomly choosing the parameters of defining the shearing field, we are able to generate numerous folded reflectivity models with various structures.

Simulate collapsed-paleokarst structures

To simulate a collapse chimney tube in the 3D reflectivity model, we construct a 3D vertically elongated ellipsoid

\[
 f(p) = (p - c)^T R^T A R (p - c),
\]

(1)
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where the values of $r_x$, $r_y$, and $r_z$, respectively, are randomly chosen from the predefined ranges to construct ellipsoids with different sizes. $R$ is a rotation matrix that potentially rotate the ellipsoid around the $x-$ and $y-$axis. By randomly choosing all the parameters in equation 1, we are able to construct numerous possible ellipsoids with various shapes, sizes, orientations, and locations. In addition, a practical collapsed-paleokarst chimney tube is not a perfect ellipsoid, we therefore randomly add some smooth perturbations to obtain irregular ellipsoids as shown in Figure 1f.

After defining the 3D tube areas of the collapsed-paleokarst chimneys, we then define the sag structures within the chimney tubes. The sag structures are typically downward bending. We therefore vertically shift the reflectors (inside a chimney tube) downward as follows to obtain a reflectivity model $r_k(x,y,z)$:

$$r_k(x,y,z) = r(x,y,z + s_k(x,y,z)),$$

where the vertical shifts $s_k(x,y,z)$ are defined as

$$s_k(x,y,z) = \begin{cases} 
0, & \text{if } f(x,y,z) > 1 \\
\gamma(f(x,y,z) - 1) + \epsilon(x,y,z), & \text{if } f(x,y,z) \leq 1 
\end{cases}$$

(5)

In this equation, $f(x,y,z)$ is the ellipsoidal function defined in equation 1. $\gamma$ is a positive scalar that is randomly chosen from the range [10, 20]. The first term of $\gamma(f(x,y,z) - 1)$ vertically shears the reflectors within karst chimneys so that they are smoothly curved downward as those shown between the cyan dashed lines (cylindrical faults) in Figure 1c. Such generated sag structures will produce clear circular features or onion rings on the horizontal slice as denoted by the red arrows in Figure 1c. $\epsilon(x,y,z)$ is a random perturbation field to simulate potential fractures or faults that dislocate reflectors within the chimney tubes (as denoted by magenta arrows in Figure 1c).

With this method, we are able to automatically simulate various collapsed-paleokarst features (as in Figure 1c) which look realistic and are comparable to the real paleokarst features in the field seismic images.

Training datasets

From a reflectivity model (Figure 1c), we then simulate a synthetic seismic image (Figure 1d) by convolving a frequency-varying Ricker wavelet with the reflectivity model and adding some noise. As the collapsed-paleokarst features are generated by well-defined functions, we can automatically obtain a corresponding binary label image (Figure 1e), from which we can further automatically obtain the 3D bodies of the paleokarst chimney tubes (Figure 1f) by simply extracting the isosurfaces (with isovalue 0.5) of the label image using the method of marching cubes (Lorensen and Cline, 1987).

To train our CNN for paleokarst segmentation, we generate 120 pairs of datasets, 100 pairs for training and the rest for validation. Figure 2 shows 8 pairs of the automatically generated training datasets. The noise in the first and second rows of images is extracted from field seismic images and randomly generated, respectively. In order to further increase the diversity of the training and validation datasets, we rotate the image around the vertical axis by 0°, 90°, 180°, and 270°. In addition, the dimension size of each generated image is 256 × 256 × 256 (samples). However, we train the CNN by using smaller images with 128 × 128 × 128 (samples) to save GPU memory and computational costs during the training. We therefore randomly cut 128 × 128 × 128 sub-images from the generated larger images during the training, which significantly increase the number and diversity of the training datasets as well.

Figure 1: The proposed workflow of generating synthetic training datasets.

Figure 2: Automatically generated synthetic training dataset pairs of seismic images and the corresponding binary label images of paleokarst features.

with which we define the 3D tube area of a chimney as follows:

$$\begin{cases} 
\text{if } f(p) \leq 1 : \text{inside chimney tube} \\
\text{if } f(p) > 1 : \text{outside chimney tube} 
\end{cases}$$

(2)

In the ellipsoidal function (equation 1), $p = (x,y,z)$ represents the coordinates of a point in the 3D reflectivity model. $e = (r_x, r_y, r_z)$ represents the center of the ellipsoid, which is randomly chosen within the 3D space of the model. $A$ is a diagonal matrix defined by the three radii of the ellipsoid as follows:

$$A = \begin{bmatrix} 
1/r_x^2 & 0 & 0 \\
0 & 1/r_y^2 & 0 \\
0 & 0 & 1/r_z^2 
\end{bmatrix}.$$

(3)
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Figure 3: To detect the collapsed-paleokarst features from the input seismic image, we design a deep CNN with the architecture of a U-net followed by two residual blocks.

Figure 4: Synthetic validation seismic images (first column), predicted (second column) and ground truth (third column) of collapsed-paleokarst features.

Figure 5: A 3D seismic image (a), acquired at the central Fort Worth Basin, is displayed with a paleokarst probability image (b) computed by using our CNN-based method. The vertical sections in (c) and (d) are extracted at the lines AA’ and BB’ that cross a large paleokarst chimney as denoted in (a) and (b).

DEEP LEARNING FOR DETECTING KARST FEATURES

We consider the detection of collapsed-paleokarst features in a 3D seismic image as a binary segmentation problem. We design a deep CNN, as shown in Figure 3, to detect the collapsed-paleokarst features in a 3D seismic image. The architecture of the designed CNN consists of a U-shape network followed by two residual blocks.

Network architecture and training

The architecture of the 3D U-shape network is modified from the original 2D U-net proposed by Ronneberger et al. (2015) for 2D medical image segmentation, which makes it applicable to our 3D problem. Compared to the original U-net, we reduce the number of layers and the number of features at each layer to significantly save memory and computational costs which is especially important for our 3D seismic image segmentation problem. We train our network by using a regular cross-entropy loss which is optimized by using the Adam method (Kingma and Ba, 2014) with a learning rate of 0.0001. We train the network with 25 epochs and each epoch goes...
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Through all the 400 training datasets including the original im-

ages and rotated images. At each epoch, each training image
with a smaller size $128 \times 128 \times 128$ is cut from a generated
larger image (with the size of $256 \times 256 \times 256$ as in Figure 2)
at a random location. Therefore, the training images at differ-
ent epochs are mostly variant.

Applications
On two new synthetic seismic images (first column in Fig-
ure 4), the predicted paleokarst features (second column) by
our trained CNN match well with the true paleokarst features
in the label images (third column of Figure 4).

Figure 5a shows the first 3D field seismic image (acquired at
central Fort Worth Basin) where the cylindrical faults (cyan
lines bounding the karst chimneys) are manually interpreted.
The karst probability image (Figure 5b), computed from seis-
mic image by the trained CNN, accurately highlight the karst
chimneys. The boundaries of the detected chimneys are highly
consistent with the manual interpretation as in Figure 5b and
a zoomed-in view of two vertical sections (Figures 5c and 5d)
extracted from the 3D images. From the probability image
(Figure 5b), we can further extract the 3D karst chimney tubes
(Figure 6a) by simply extracting the isosurfaces (with an iso-
value of 0.5) using the method of marching cubes (Lorensen
and Cline, 1987).

Figure 7 shows another field seismic image (acquired at the
northern Fort Worth Basin) and the corresponding karst prob-
ability image (Figure 7b) computed by the CNN model trained
on only synthetic datasets. Figures 8a and 8d display two
vertical seismic sections (extracted along the lines A (blue)
and B (red) as denoted in Figure 7) where the boundaries of
the karst chimneys are manually interpreted by (McDonnell
et al., 2007). In the corresponding karst probability images
(Figures 8b and 8e) computed by our CNN model, the karst
chimneys are clearly highlighted. The contours (cyan curves
in Figures 8c and 8f), extracted from the probability image at
the porbability value of 0.5, delineate the boundaries of the
paleokarst chimneys, which are consistent with the manually
interpreted concentric faults (dashed black lines in Figure 8a
and 8d) that bounds the chimneys. Figure 9a shows a hori-
zontal slice of coherence (Figure 9a) and our karst prob-
ability (Figure 9b), where the later provides a much better detec-
tion of circular karsts than the former. By extracting the con-
tours (with a probability value 0.5) from the probability slice,
we automatically obtain the karst boundaries (cyan curves in
Figure 9b) which are consistent with the manual interpreta-
tion (white curves) in Figure 9a. With the probability im-
age(Figure 7b), we can further automatically extract 3D karst
chimney tubes (Figure 10a), from which we can automatically
estimate the geometric parameters of the paleokarst system
such as the length and width as marked in Figures 10b and 10c.

CONCLUSIONS
We propose a deep CNN for paleokarst delineation in seismic
images which is much superior to conventional methods. To
train the CNN, we propose an efficient and effective workflow
to automatically generate structural models with realistic fold-
ing structures and paleokarst features and further create rich
training datasets which are freely available through the link
https://doi.org/10.5281/zenodo.3690252. The CNN,
trained with only synthetic datasets, works well in field seismic
images to detect paleokarst features from which we can auto-
matically extract the 3D boundary of each paleokarst chimney
tube and quantitatively measure its geometric parameters.
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