RESEARCH ON FRACTURE RECOGNITION IN WELL LOGGING IMAGES: ADVERSARIAL LEARNING WITH ATTENTION

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ABSTRACT

Semantic recognition of fractures in well logging images is vital for engineers to implement oil and gas exploration. An essential approach to accomplishing the object is to adopt deep learning based on convolutional neural networks. However, due to the lack of annotated labels in well logging images, it is scarcely available to directly train the semantic segmentation network. In this paper, we explore a domain shift model attempting to achieve domain adaptation from one annotated dataset to our target well logging images. This model's core is to utilize adversarial learning, including generator and discriminator, which can prompt the model to generate fracture segmentation similar to the source domain in the target domain. For enhancing the domain adaptive model further, an attention module is introduced, which can suppress redundant noise in semantic segmentation results. We demonstrate that our proposed model performs well by extensive tests and ablation experiments in the ultrasonic well logging images.

Index Terms— fracture recognition, semantic segmentation, adversarial learning, attention.

1. INTRODUCTION

In terms of reservoir formation and evolution, faults with their controlled fracture development zones are crucial oil and gas storage spaces where oil and gas can flow and gather [1]. According to this feature, for a long time, engineers have been attempting to seek effective and accurate ways to determine natural fractures in oil and gas exploration, which have prompted several techniques such as subsurface electromagnetic technique, tiltmeter, downhole microseismic fracture monitoring, radiotracer diagnosis and image well logging. Compared with other exploration approaches, ultrasonic image well logging [2] is a competent method that yields intuitive well logging results to identify geological fractures or other features through visual observation. This well logging tool draws the borehole wall image by measuring the arrival time and amplitude of ultrasonic echo, as shown in Figure 1.

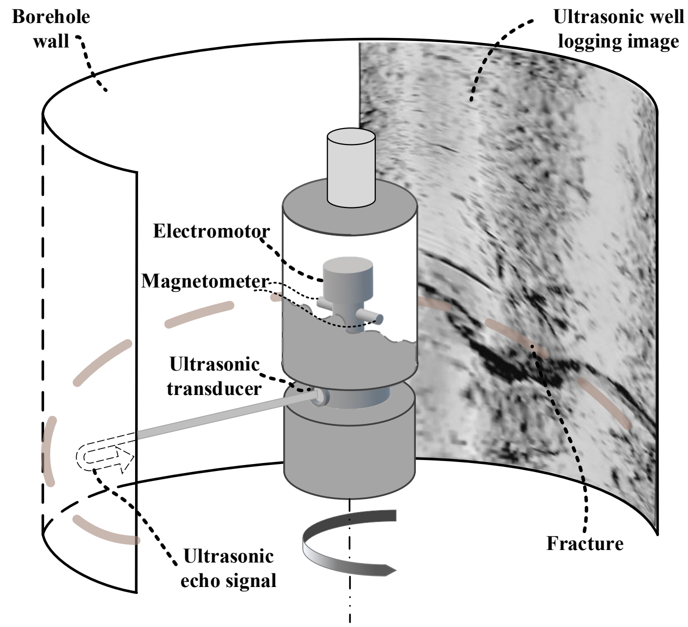

Fig. 1. The principle of ultrasonic image logging.

A challenge for researchers is to automatically pick the fractures in well logging images as it is considerably prohibitive and time-consuming by manual. To date, plenty of existing methods have been applied to this task such as hough transform [3], ant colony algorithm [4], directional filtering [5], etc. These aforementioned methods utilize single content information merely like theoretic curve shape, a connected region in logging images or other features, which have great contribution to fracture recognition but still have room for improvement. Therefore, image semantic segmentation by mining high-dimensional information is necessary to improve fracture recognition in well logging images. Resulting from the rapid advances in deep learning, especially as the development of convolutional neural network (CNN), semantic segmentation based on CNN has been improved significantly, which can perform pixel-wise classification more precisely. Fully convolutional neural network (FCN) [6], U-net[7], SegNet[8], etc. were proposed successively and showed promising results. In our work, duo to the shortage of annotated labels in well logging images, we consider transfer

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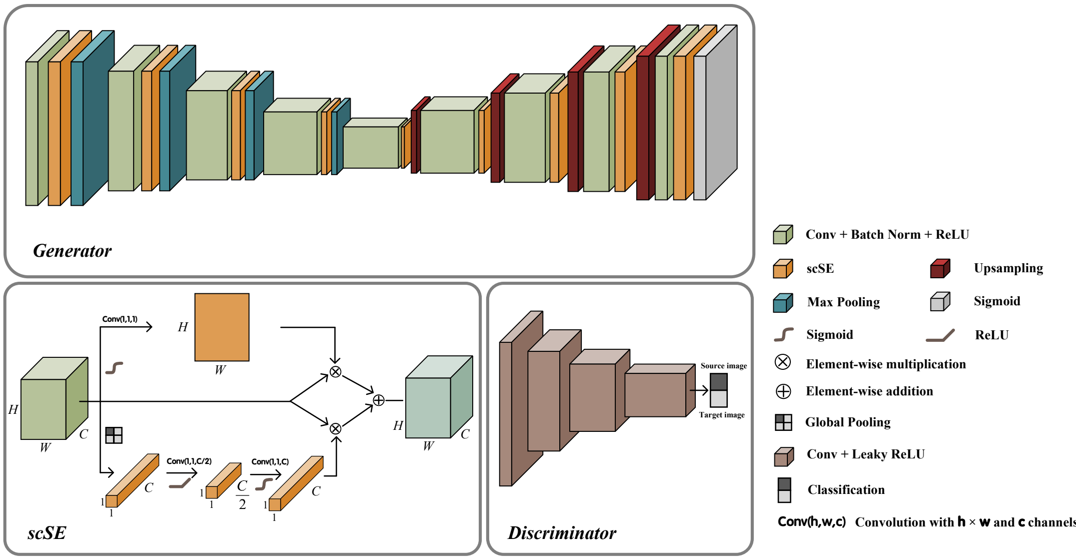

Fig. 2. The framework of ALA.

learning, especially unsupervised domain adaptation [9], to deal with this task. In this paper, a domain shift model termed Adversarial Learning with Attention (ALA) is built, which is motivated by [10] and conducts domain adaptation between crack dataset with labels and our well logging images. The entire model consists of the generator (***G***) and discriminator (***D***) which employ a Encoder-Decoder architecture and a fully convolutional network respectively. For boosting segmentation further, an attention module is applied to ***G***, which tends to suppress irrelevant noise. After training in the source domain and target domain alternately, our method performs favorably in fracture recognition and extraction.

The following parts of this paper comprise that section 2 depicts this model's detailed architecture, section 3 presents the datasets, section 4 presents experimental results, and section 5 summarizes the research.

2. METHOD

As mentioned above, the ALA model, comprising ***G*** and ***D*** , adopts adversarial learning to decrease distribution differences between source domain and target domain. ***G*** with attention module and ***D*** are responsible for generating semantic fracture segmentation and identifying which domain the image belongs to, respectively. We conduct domain adaptation at the output level of ***G*** aiming to fool ***D*** into making the wrong judgment as possible. The entire architecture of this model is illustrated in Figure 2.

G based on a U-net like encoder-decoder structure is shown in the top half of Figure 2. In ***G***, the conv-blocks painted green have two convolution layers, Batch Norm layers and ReLU functions respectively. The channel number is {64,128,256,512,1024} in the encoder, and the mirrored structure exists in the corresponding decoder. Different from the typical U-net, inspired by [11], every conv-block is followed by a spatial and channel 'squeeze and excitation' (scSE) block painted yellow, which is used to boost meaningful fractured shapes. The scSE is constituted by channel-wise squeeze and excitation (cSE) and spatial-wise squeeze and excitation (sSE), which pay more attention to important channels and emphasize appropriate spatial locations, respectively, as shown in the lower left of Figure 2. For ***D***, it utilizes a fully-convolutional architecture which consists of 5 convolution layers with 4×4 kernel, where the channel number is {64,128,256,512,1}, respectively. A leaky ReLU is selected as the activation function following every convolution layer except for the last one, illustrated in the lower right of Figure 2.

The alternate training process of the ALA model is divided into three steps. First, source images with annotated labels are passed into ***G*** to optimize the segmentation loss L_{seg},

$$L_{seg}\left(g_s\right) = -\sum_{h,w}\sum_{c\in 2} T_s\left(h,w,c\right)\log\left(p_s\left(h,w,c\right)\right), \quad (1)$$

where T_s is the ground truth in source domain, $p_s = \boldsymbol{G}(g_s)$ is the segmentation output, and c denotes two pixel-wise categories corresponding to fractures and background. Second, to fool ***D***, we forward target images to ***G*** and gain the $p_t = \boldsymbol{G}(g_t)$. Then, an adversarial loss L_{adv} is proposed to confuse the distribution of p_s and p_t, as shown in Equation 2,

$$L_{adv}\left(g_t\right) = -\sum_{h,w}\log\left(\boldsymbol{D}\left(p_t\right)\left(h,w,0\right)\right), \quad (2)$$

where 0 represents the image comes from source domain and 1 represents the image is from target domain. Obviously,

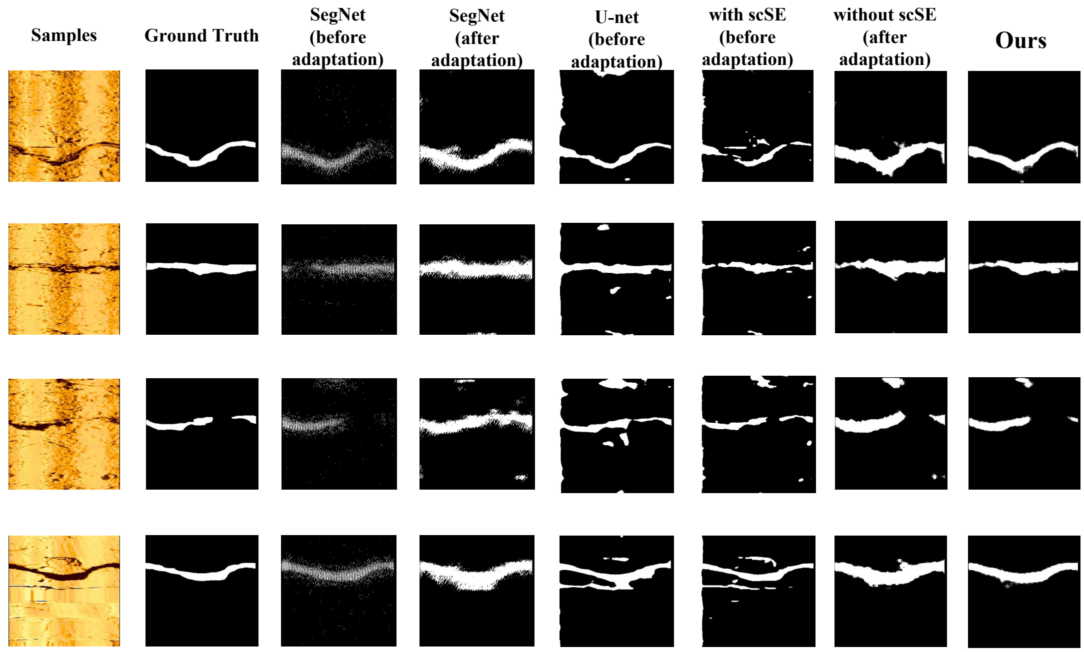

Fig. 3. Typical results of segmentation using different strategies. From left to right columns: Raw images, ground truth annotations, SegNet before adaptation, SegNet after adaptation, U-net before adaptation, applying scSE before adaptation, without scSE after adaptation, and our method.

given the opposite category label, $\boldsymbol{D}$ tends to make wrong judgments. Finally, source images and target images are forwarded to $\boldsymbol{G}$ to generate segmentation output, which is given to $\boldsymbol{D}$. $\boldsymbol{D}$ calculates the loss value with corresponding category label and optimizes the category loss L_c,

$$\begin{aligned} L_c\left(g_t, g_s\right) = -\sum_{h,w} &(1-z)\log\left(\boldsymbol{D}\left(p_s\right)(h,w,0)\right) \\ &+z\log\left(\boldsymbol{D}\left(p_t\right)(h,w,1)\right), \end{aligned} \tag{3}$$

where z denotes the category of the input image. The final purpose aims to minimize L_{seg} for source images, while maximizing L_{adv} and L_c to make $\boldsymbol{D}$ produce the wrong classification judgment, as shown in equation (4),

$$\max_{D}\min_{G}\left(L_{seg}\left(g_s\right) + L_{adv}\left(g_t\right) + L_c\left(g_t, g_s\right)\right). \tag{4}$$

After trained, in the inference phase, only the generator is utilized to perform semantic fracture segmentation. The parameters and FLOPs of the generator are 32.79M and 51.67G respectively. The code of this paper is available at `https://github.com/BladeLee6913/ALA`.

3. DATASETS

In this paper, CRACK 500 we employed as source datasets comprise 1895 road images with pixel-wise semantic road crack annotations [12], which possess similar distribution to target well logging images. In annotated labeling images, the pixel painted white denotes the region belongs to fractures, and the rest of the labeling images is background painted black. The target well logging images are supplied by China Oilfield Services Limited (COSL), collected from 4423 meters to 4559 meters under-ground in the Zhanjiang production well. The target image dataset consists of 72 images resized to a spatial resolution of 352×352 consistent with source images. Training of the model bases on PyTorch 1.2 framework and python 3.7. The entire training test is carried out on an i9-9900k CPU with 64GB RAM and RTX 2080Ti with 11GB RAM.

4. EXPERIMENTS AND RESULTS

For demonstrating our method's satisfactory performances, U-net as a baseline approach was implemented compared with ours, which is a common strategy based on CNN for supervised semantic segmentation. All tests were divided into two stages corresponding to before and after domain adaptation, respectively. At each stage, ablation experiments in which the scSE module was used or removed were conducted to show its fracture segmentation effectiveness. All strategies mentioned above were trained for 50 epochs, respectively, and the batch size was set to 4. The learning rate was set as 2.5×10^{-4}, and the optimizer selected was Stochastic Gradient Descent (SGD). Typical results of fracture extraction in the target domain are illustrated in Figure

Table 1. Accuracy assessment for domain adaptation.

Parameters	F1 score	Mean IOU(%)
SegNet (before adaptation)	0.49	32.57
SegNet (after adaptation)	0.61	44.53
U-net (before adaptation)	0.64	47.82
with scSE (before adaptation)	0.65	48.42
without scSE (after adaptation)	0.73	59.32
Ours	0.79	67.18

3. By comparing our trained model with other diverse strategies, all segmentation results of fracture extraction interpret that adversarial learning can assist semantic segmentation network in determining fracture region. The proposed model accomplishes domain adaptation by sharing similar features between source road crack annotations and target fractures in well logging images, and scSE can recalibrate fracture shape and yield a consistent visual improvement.

F1 score and Mean IOU, shown in Table 1, are calculated to demonstrate the necessity of considering the domain shifting and applying the attention module. Based on our proposed model, the IOU can be increased from 32.57 to 67.18, and the F1 score can be increased by 0.3. All the above results demonstrate that for fracture recognition in well logging images, it is feasible to perform domain adaptation by adversarial learning and share adapted weights to extract fractures. And U-net is more appropriate as a generator than SegNet while considering F1 score and Mean IOU. Furthermore, the scSE module can suppress irrelevant features and yield clearer fracture extraction.

5. CONCLUSION

In this paper, a domain shift model is proposed for fracture recognition in well logging images without annotated labels. The model adopts adversarial learning by alternately training generator and discriminator to optimize the semantic segmentation network for similar fracture extraction between these two domain datasets. Meanwhile, the scSE module is applied to the segmentation network, which improves fracture segmentation results by paying more attention to meaningful information existing spatial regions and channels. Considering several differences between source road crack and fractures in the well logging images, we will further investigate how to improve the results with other domain adaptation methods. In particular, we will attempt to make it possible to deploy the trained model in embedded systems by reducing the network size.

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