Automatic Fault Detection using Semantic Segmentation based UNET Model with a Strong Backbone Network

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Keywords

Deep learning, DENSENET121, Fault accuracy index, Fault interpretation, INCEPTION-v3.

Abstract

Seismic faults are among the core geological features of interest for the geophysicist for efficient seismic interpretation. They are formed by the displacement of the adjacent blocks of rocks. Because faults may seal the porous reservoir rocks, they indicate the probable availability of hydrocarbons. Accurate fault detection is the utmost important step as drilling well is a very expensive venture, and false fault detection may result in drilling dry well and cause huge losses. The seismic survey area is also expanding to fulfill the increasing demand for petroleum products with the growing population. The traditional methods require interpreters and geophysicists to label each fault manually, which is practically tedious, cumbersome, and time-consuming. Moreover, human intervention is prone to errors. Hence, it is paramount to reduce such possible howlers while detecting seismic faults.

Introduction

Seismic faults are among the core geological features of interest for the geophysicist for efficient seismic interpretation. They are formed by the displacement of the adjacent blocks of rocks. Because faults may seal the porous reservoir rocks, they indicate the probable availability of hydrocarbons. Accurate fault detection is the utmost important step as drilling well is a very expensive venture, and false fault detection may result in drilling dry well and cause huge losses. The seismic survey area is also expanding to fulfill the increasing demand for petroleum products with the growing population. The traditional methods require interpreters and geophysicists to label each fault manually, which is practically tedious, cumbersome, and time-consuming. Hence, it is paramount to reduce such possible howlers while detecting seismic faults.

In the past decade, a colossal amount of work has been devoted to seismic interpretation by introducing various seismic attributes, signal processing, and machine learning algorithms to delineate faults. Seismic attributes are the quantities computed or implied from the seismic characteristic of interest. They obtain geological features of interest that aid in fault interpretation. Dip, azimuth, curvature (Roberts, 2001), variance, coherence using cross-correlation (Bahorich et. al., 1995), semblance (Marfurt et al., 1998), Eigen-structure analysis Gersztenkorn, Marfurt, 1999), gradient structure tensor (Singh et al., 2022) are some of the seismic attributes that help highlight faults from seismic data. Few works of attribute enhancement such as Gaussian-Hermite moments (Yang et al., 2011), multispectral coherence (Lyu B. et al., 2020) etc. are used to enhance the attribute resolution. This further helps in delineating faults using signal processing and machine learning techniques. Signal processing techniques such as Hough transform (Wang Z, AlRegib G, 2014), visual saliency are employed, whereas multi-attribute based machine learning techniques involved patch-based multi-layer perceptron, support vector machine (Di H., 2019) for fault delineation. In recent years, deep learning methods have been grabbing attention in many fields. Convolutional neural network (CNN) based semantic segmentation has been employed for seismic fault detection. Some of the works include fault detection using UNET (Li et al., 2019), UNET++ (Yang et al., 2020), and ensemble learning (Li et al., 2022) etc. The drawback with previous works is that they require a large, labeled dataset which is not feasible for a geophysicist to label every pixel of seismic volume. Few of the works addressed this issue with training only on a labeled synthetic dataset, but it fails to delineate faults in real field test seismic datasets. Other CNN models are either very complex or require many trainable parameters.

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In our proposed method, we use the blend of very few labeled real field and synthetic seismic sections for training and validation. To create the final UNET, vannila networks such as densenet, inception etc. networks are taken, and their counterparts are formed to execute decoding and upsampling via deconvolution. A new similarity metric has been proposed in this paper, known as the fault accuracy index. This helps to validate our results compared to previous work mentioned in Wu et al., (2019) and ground truth.

Proposed Method

Few inline sections of real field seismic dataset are labeled by a geophysicist. Along with the real field seismic data, synthetic seismic sections are used to train the UNET model with a strong backbone network such as INCEPTION-v3, DENSENET121. These CNNs create the encoder part and capture the features better. UNET exhibits a better performance in semantic segmentation compared to LinkNet, pyramid scene parsing network or feature pyramid network as it adopts channel dimension splicing and fusion method to extract subtle and minor features. We have also proposed a new method of fault accuracy index to ascertain the effectiveness of the CNN model which will be discussed in subsequent sections.

Semantic segmentation classifies each pixel in an image. This phenomenon is used in binary classification to classify fault and non-fault pixels in a seismic image. The semantic segmentation can be employed using various CNN models such as UNET, FPN, Linknet, Segnet, etc. Many studies have shown that UNET works better in semantic segmentation. Hence, Wu et al., (2019) have employed UNET in seismic fault detection. UNET is an encoder-decoder architecture consisting of a contracting path for feature extracting and symmetrical expansive path for upsampling. During upsampling in the expanding path, spatial information recreated is imprecise. To counteract this problem, the UNET uses skip connections that combine spatial information from the downsampling path with the upsampling path. However, this brings across many redundant low-level feature extractions, as feature representation is poor in the initial layers.

Workflow using UNET with a Strong Backbone

The backbone networks such as Densenet and Inception-v3 are extensively researched and widely used CNN models serve as the encoder part, and the decoder part is symmetrically constructed as per the encoder. First, the data is undergone seismic pre-processing, and seismic patches are labeled and selected for training. The UNET model with a backbone network is trained and tested on synthetic and real field seismic data. We also propose a new fault similarity method known as fault accuracy index to validate the performance of our model.

1. Preprocessing:

- Step 1: Modified spectral balancing (Mahadik et al., 2021) to obtain the salient and subtle features in the CNN encoder part.
- Step 2: Fault labeling of real field seismic patches. Each pixel needs to be labeled into binary class i.e., fault (1) and non-fault (0).
- Step 3: Generate 2-D real-field and synthetic seismic patches with patch size $m \times m$.

2. Data Augmentation:

CNN models require many samples to get better accuracy. It is not feasible for a geophysicist to label a substantial number of samples. Wu et al., (2019) used only synthetic samples and trained the network with them. But training on synthetic data creates a bias towards detecting faults in real field seismic data, and unnecessary seismic events may be generated. To address this issue, we propose the data augmentation of the real field seismic patches to increase the diversity of training samples and improve the robustness of the network. We have chosen three methods for data augmentation i.e., horizontal flipping, vertical flipping, and random rotation -30 to 30 degrees. As we have a considerable amount of synthetic seismic images, we apply data augmentation only on real field seismic images.

3. Training

We train our model by keeping a strong backbone of Inception-v3 and DENSENET121 as an encoder. The decoder part does the upsampling by implementing convolution transpose along with skip connections connected from an encoder.

An inception network is a CNN model with the architectural design consisting of repeating components known as inception module (Szegedy et al., 2015). A model is overfitted when multiple deep layers of convolutions are used in the model. To address the issue, the inception model employs the idea by using multiple filters of different sizes on the same level. We have used the Inception-v3 model (Jignesh C. et al., 2020), an advanced and optimized version of inception network, consisting of 42 layers that have higher efficiency than previous inception networks, computationally less expensive, and uses auxiliary classifiers as regularizers.

Densenet architecture connects all the layers densely, i.e., each layer receives inputs from all preceding layers and propagates the feature information to all subsequent layers. We use DENSENET121 architecture, which alleviates the vanishing gradient problem, obtains more diversified features, strengthens feature propagation, encourages feature reuse, and substantially reduces the number of trainable hyper-parameters.

4. Binary Cross-entropy with Jaccard Loss

The number of fault pixels in any labeled seismic data will be significantly lesser than the non-fault pixels. To address the issue of class imbalance, we employ the sum of binary cross-entropy (BCE) and Jaccard loss (Jaccard) as the loss which is defined as follows:

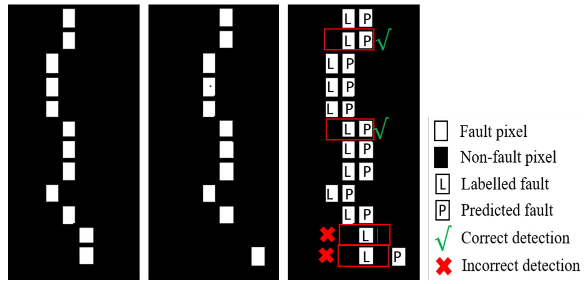
$$\mathrm{BCE}(Y,\hat{Y}) = -\frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{2}.Y_i.\log\hat{Y}_i\right)$$

$$\mathrm{Jaccard}(Y,\hat{Y}) = 1 - \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i.\hat{Y}_i + \epsilon}{Y_i + \hat{Y}_i - Y_i.\hat{Y}_i + \epsilon}$$

where Y_i and $\hat{Y}_i$ denote the flattened labeled ground truths by a geophysicist and flattened predicted probabilities of the i^{th} seismic section respectively. N denotes the batch size, and ϵ is the smoothness which is set to 10^{-3}.

5. Fault Accuracy Index

Validation of the detected faults in the seismic data is crucial. The classical method to calculate true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are not the correct way to validate. Fig. 1 depicts such case in which Fig. 1a shows the labelled fault seismic patch and Fig. 1b shows the predicted fault seismic patch. Notice that faults in Fig. 1b are shifted to the right by one pixel. As our proposed algorithm classifies each pixel into fault or non-fault class, the total number of true positives will be 0 even though this fault detection will be perfectly acceptable by a Geophysicist. So, we propose a new metric known as fault accuracy index, which works on the same principle as intersection over the union.



(a) (b) (c)

Figure 1: (a) Labeled seismic patch. (b) Predicted seismic patch. (c) Illustration of fault accuracy index calculation.

In our proposed method of calculating TP, FP, FN, and TN, we calculate the F-1 score metric.

$$\mathrm{TP}{+}{=}\ 1 \text{ if } P\left(x_{L_f}, y_{L_f} \pm R\right) \in \text{Fault pixel}$$

$$\mathrm{FP}{+}{=}\ 1 \text{ if } P\left(x_{L_{nf}}, y_{L_{nf}} \pm R\right) \in \text{Fault pixel}$$

$$\mathrm{FN}{+}{=}\ 1 \text{ if } P\left(x_{L_f}, y_{L_f} \pm R\right) \in \text{Non-fault pixel}$$

$$\mathrm{TN}{+}{=}\ 1 \text{ if } P\left(x_{L_{nf}}, y_{L_{nf}} \pm R\right) \in \text{Non-fault pixel}$$

where $P(\cdot,\cdot)$ is the predicted seismic patch $\left(x_{L_f}, y_{L_f}\right)$ and $\left(x_{L_{nf}}, y_{L_{nf}}\right)$ is the fault and non-fault pixel index position of labeled seismic patch respectively. R denotes the search radius as illustrated in Fig. 1c.

Experimental Results & Discussion

A popular deep learning framework TensorFlow is used. All models are trained on an NVIDIA A40 GPU with 48 GB RAM. The ADAM optimizer is selected with a constant learning rate throughout all the epochs and set as 10^{-3}, and the number of epochs is 40. Batch normalization is used in the decoder type to make the model faster and more stable. Batch size is set as 10, and the number of trainable hyperparameters for Inception-v3 is ~24.5M where that of DENSENET121 is ~8.5M. Finally, the fault accuracy index is calculated for each patch and compared with previous work by Wu et al., (2019).

A. Dataset Description

3D processed post-stack time migrated volume consisting of 2601 crosslines & 2536 inlines, located

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in the offshore Krishna Godavari (K.G.) Basin is used in this article proprietary to Oil and Natural Gas Corporation (ONGC) Ltd., India. The sampling time interval is 4 *ms*, and the data is recorded up to 4 *s*.

B. Fault Prediction on Real-Field Data

First, all the models (including the UNET model proposed in Wu et al., (2019) are trained using the amalgamation of real-field and synthetic dataset of patch size 200 x 200. The networks form the encoder structure with filter lengths 64, 32, 16, 16, 32. Larger filter banks increase the time and the computational complexity. 1000 synthetic and 120 real field annotated seismic data are used for training. The real field seismic data are augmented, and the sample size is increased to 840. With the 1840 labeled seismic patches, the data is split into 70% training and 30% validation dataset. Once the models are trained, the network is tested on various seismic patches, as illustrated in Fig. 2.

The first column in Fig. 2 illustrates the seismic patches; the second column shows its corresponding manually labeled faults by expert geophysicists; the third column shows the results obtained using the basic UNET model proposed in Wu et al., (2019), fourth and the fifth column displays the experimental results obtained using our proposed method with Inception-v3 and DENSENET121 respectively. Green ellipses denote the absence of the fault (false negative) as illustrated in Fig. 2c, Fig. 2h, Fig. 2r, Fig. 2w whereas the red ellipses denote the present of the fault (false positive) as illustrated in Fig. 2c, Fig. 2m, Fig. 2r. The false negatives and false positives are mostly present in the fault delineated seismic patches obtained using Wu et al., (2019) that have been addressed by our proposed method. The ellipses are shown only when the majority of the fault part is either generated (red ellipses) or missed (green ellipses). In Fig. 2w, the faults are merged which is alleviated in Fig. 2x and Fig. 2y. The fault accuracy metric analysis is shown in table 1. At some instances such as Fig. 2h-2j, Inception-v3 based UNET performs better than basic UNET and DENSENET121 based UNET whereas in all other instances, DENSENET121 based UNET performs better than basic UNET and Inception-v3 based UNET. We prefer DENSENET121 model over Inception-v3 because of the former gives better results in a very less number of trainable hyperparameters. Moreover, transposed convolution is used instead of upsampling because the spatial information recreated in upsampling is imprecise and thus is propagated in subsequent layers. But, transposed convolution gives better resolution and detection of the features and loss is mitigated during tuning the trainable parameters. As the fault and non-fault pixels are highly imbalanced, we have used the F-1 score metric to determine the effectiveness of the CNN models. Our proposed algorithm is not only effective in detecting subtle and minor faults, but also no post-processing methods are used to further refine the results, sharpen the faults, and/or remove any unwanted, spurious events.

Table 1: Comparison of Fault Accuracy Metrics on Various Real-Field Seismic Patches

Patch No.	Backbone CNN Model for UNET	F-1 Score
Fig. 2a	FaultSeg3D (Wu et al., 2019)	63.49%
	Inception-v3	81.78%
	DENSENET121	**84.32%**
Fig. 2f	FaultSeg3D	50.65%
	Inception-v3	**75.96%**
	DENSENET121	64.21%
Fig. 2k	FaultSeg3D	67.02%
	Inception-v3	97.31%
	DENSENET121	**97.95%**
Fig. 2p	FaultSeg3D	58.06%
	Inception-v3	68.60%
	DENSENET121	**81.93%**
Fig. 2u	FaultSeg3D	77.16%
	Inception-v3	78.19%
	DENSENET121	**81.21%**

Conclusions

In this article, we have proposed a semantic segmentation method using UNET with a strong network Inception-v3 and DENSENET121 to delineate faults from the seismic data. These backbone networks form the encoder part of the UNET and extract every subtle and minor features of the seismic patches. The expansive path of the UNET is created as per the encoder and the upsampling is done using transposed convolution which offer super

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resolution algorithms and accurate semantic segmentation. The backbone networks detect the faults accurately and perform better than previous state-of-the-art methods, traditional machine learning techniques and basic UNET model proposed by (Wu et al., 2019). This article does not compare between two backbone networks but compares with the basic UNET model. We find that the both the backbone networks can detect the very subtle and minor faults which is one of the major contributions. The novel approach to find the fault detection accuracy metric is proposed and validated with the aid of the experimental results on real-field seismic data. In future, we intend to work on graph-based deep learning methods and generative adversarial networks.

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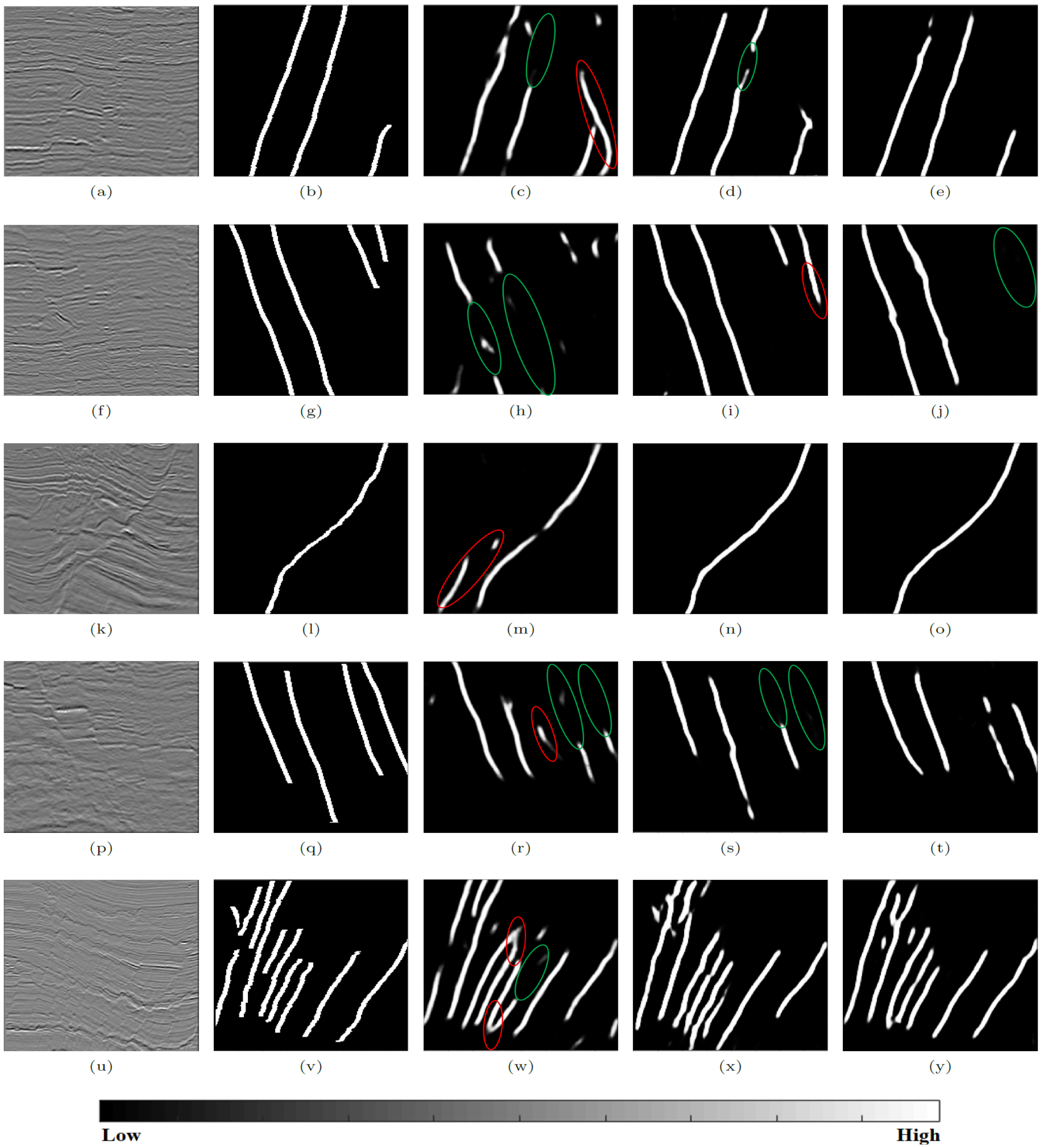

Figure 2: (a), (f), (k), (p), (u) seismic patch. (b), (g), (l), (q), (v) Manually labeled faults. (c), (h), (m), (r), (w) Predicted faults using Wu et al., (2019) (d), (i), (n), (s), (x) Predicted faults using UNET with Inception-v3 as a backbone. (e), (j), (o), (t), (y) Predicted faults using UNET with DENSENET121 as a backbone. Green ellipses denote the absence of the fault (false negative) whereas the red ellipses denote the present of the fault (false positive).