



A Convolutional Neural Network Approach for Stratigraphic Interface Detection

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Abstract. Making full use of the remaining oil-gas resources is a practical and feasible way to solve the problem of oil shortage. And the most important step of this method is the accurate detection of stratigraphic interface. In this paper, we propose a Convolutional Neural Network (CNN) approach for stratigraphic interface detection from the geophysical well logging data. Our proposed approach can automatically extract representative features from well logs data. It can reduce errors caused by human factors such as manual randomness and lack of experience. First of all, we normalize the data in the form of a single point of the well logging data and convert data points to 2D segment. We then feed segments into the CNN model for training. Secondly, we predict the formation of the well logging data using the trained model. Finally, we introduce a post-processing method to perform the stratigraphic interface detection. The experimental results demonstrate the proposed approach is able to achieve 89.69% of the average accuracy of stratigraphic interface detection. Moreover, the relative error between the predicted boundary points with the ground-truth is only 1%, which indicates the proposed approach satisfy the real-world application requirements.

Keywords: Stratigraphic interface detection · Geophysical well logging · Convolutional Neural Network

1 Introduction

Nowadays, various high-tech technologies emerge sequentially with the rapid development of the world economy. This is the reason why the consumption of oil in various countries is increasing. To meet the needs of developing of society,

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further exploration and exploitation of the oil and gas resources is a practical and promising solution. Stratigraphic interface detection is one of the most important tasks for petroleum logging. An automatic stratigraphic interface detection can save human and material resources for the successive development of oil and gas resources.

The well logging data obtained using logging technology contain the formation properties varying with the depth of well. They directly reflect of underground geological features. Therefore, the interface detection of well logs is of great significance for accurately determining the location of the stratigraphy. For a long time, the manual interpretation methods of stratigraphic interface detection is mainly subjective judgments. These methods are mainly based on the morphological transformation characteristics of well logging data, the differences between strata, and the past experience of geologists. These conventional methods not only need huge human and material resources, but also has a relative high detection error. However, the machine learning methods provide an promising solution for automatic detection to solve these problems.

In this paper, we propose a convolutional neural network approach for stratigraphic interface detection. First of all, we normalize the data in the form of a single point of the well logging data, and convert the data points to 2D segment. We then feed segments into the CNN model for training process. Secondly, we use the trained model to predict the formation of the well logging data. Finally, we introduce a post-processing method for the stratigraphic interface detection to fine-gain the detection results. The proposed approach can automatically extract representative features from well logging data. It can reduce errors caused by human factors such as manual randomness, lack of experience, and relatively low proficiency. It can also improve the work efficiency and provide a theoretical basis and foundation for the further development of remaining oil-gas resources.

The contributions of the proposed approach can be summarized as follows. Firstly, we convert single-point well logging data point into segment. Using single points of the well logging data directly will separate the well logging and ignore the relationship between points. So in our manner, the short term temporal information can be fully combined to facilitate subsequent training operations. Secondly, we define stratigraphic interface detection as a classification problem and utilize the formulated segments as input for training CNN model. It is able to extract the effective features of all well logging data. Finally post-processing the prediction results can effectively avoid prediction errors in the prediction process. We evaluate the proposed approach on a real-world oilfield application. The experimental results show that the relative error between our predicted detection result with the ground-truth only 1%, which proves that the proposed approach satisfy the real-world application requirements.

2 Related Work

There are manual interpretation methods and machine learning based methods of stratigraphic interface detection division for well logging. The manual interpretation methods need observing the changes in the shape of the logging data

to find out the position of the half point of each section. These methods require expert knowledge and experience [20]. These methods also will cause great differences in the stratigraphy results due to differences in personnel experience and proficiency. It will bring a lot of work to the staffs and cause a lot of waste of human and material resources. As the spread of machine learning methods in well logging application, the automatic stratigraphic interface detection methods developed fairly quickly. These methods it can be mainly divided into mathematical statistics methods, non-mathematical statistics methods, and artificial intelligence methods.

Mathematical statistics consists of intra-layer difference methods, ordered cluster analysis and extreme variance clustering methods. Merriam and Hawkins used ordered cluster analysis to stratify a well log firstly [6]. The essence of this method is to seek the optimal cut point to estimate the mutation point. By using the concept of variance in mathematical statistics, the data with close regularity of variance and dispersion is regarded as one category. The data in the two adjacent classes should be obviously different. It is used as the basis for well logging segmentation. Later, they applied the algorithm to multiple well logging application [7]. It can be seen from the methodological perspective that the ordered cluster analysis is very sensitive to the error parameters, and it is easy to lead to overfitting problem. Moreover, the boundary points required by this method only satisfy the minimum intra-layer variance and the maximum inter-layer variance, without considering the geological significance of the interface, i.e., the appearance of false layers. Robert et al. proposed a method based on extreme variance clustering to divide the stratigraphic interface [8, 21]. Firstly, they separate the well log roughly, and then they found the segmented point of the precise interface. The cluster analysis method is used to subdivide the layer to realize the merging of the layer interface. This method can maintain the uniformity of the formation and the difference between the layers, but the calculation is very large. It needs to calculate the stratigraphy index for all possible stratigraphy points, and then locates the best stratigraphy interface from these points. If this method is used in the detailed layering step, the amount of calculation will be very huge.

Non-mathematical statistics methods consists of Walsh transform, activity function method, wavelet transform method, Fourier transform and so on. The activity function method was firstly used to calculate the dip angle of microelectrode logging to determine the formation interface [22]. In the process of finding the inflection points of the well log as the stratigraphy point, it can be known that the second derivative at these points is zero. In this manner, the second derivative can be obtained from the well log and the zero point can be found. However, this method is very sensitive to the selection of the window length. The activity curve with a small window length has a poor suppression of interference noise, while the activity curve with a large window length reflects the poor change in the slope of the well logs. Lanning et al. first applied the Walsh transformation to logging data to discover lithological boundaries [24]. Maiti et al. used Walsh transform to perform logging automatic stratigraphy [25].

Pan et al. combined wavelet transform and Fourier transform to achieve logging stratigraphy [26]. Qiao et al. used 3D technology to establish a stratigraphic model [4, 5]. They tried to find a consistent method for describing heterogeneity by defining a curved coordinate system that conforms to the sedimentary layer. Non-mathematical statistics methods are simple in principle, with small calculation and fast speed. However, these methods are not easy to integrate multiple well logs information.

Artificial intelligence methods include fuzzy recognition and neural network methods. Hathaway et al. identified the formation interfaces based on fuzzy clustering [9]. Based on the feature vector of each sampling point, they determined the affinity relationship of each sampling point and clustered the sampling points according to this relationship. There is no doubt that this method also has an obvious problem of large amount of calculation. Wu et al. used a simple iterative linear regression model to identify the interface, and used heuristic algorithm to filter to get the stratigraphy [27]. Zhou et al. proposed a machine learning method for stratum series simulation respectively [2, 3]. On the basis of the recurrent neural network, a sequence model of stratum types and a sequence model of stratum thickness are established. Shahab et al. [10] applied BP neural network [11, 12] to the identification of reservoir lithology. The integrated electrical measurement data is used as input of convolutional neural network to construct the within-group and between-group errors of known classified samples. Then the ratio of the within-group error to the between-group error is used as the objective optimization function to obtain the discriminant function and discriminant criterion. The classification of the flow units of the key wells to be classified is carried out at last. However, although the application of neural network to the lithology identification of reservoirs can greatly increase the calculation speed, this application method is also not suitable for all well logs. Only the well logs with better lithology recognition effect can be used to participate in the training process.

Our proposed approach belongs to artificial intelligence method. Different from the methods mentioned above, we directly process the single-point well logging data. We convert one dimensional data into two dimensions, so that combining the short term temporal information to facilitate subsequent training operations. And we define stratigraphic interface detection as a classification problem. The proposed method can not only solve the problem of large amount of calculation, but also make full use of the information in multiple well logs. The human participation factor in our proposed method is relatively small.

3 Proposed Method

The overview of our proposed approach is shown in Fig. 1. First of all, we converted the data in the form of a single point of the well logging data into 2D segments after standardizing according to the well logging. And these segments are fed into the CNN network as a single-channel picture for training. Secondly, we use the trained model to predict the formation of the well logging data.

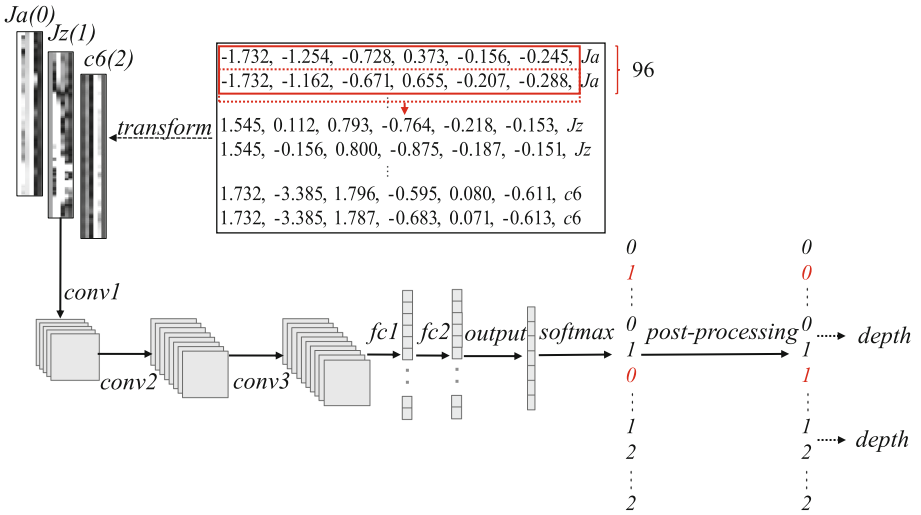


Fig. 1. The overview of our proposed approach

Finally, we detect the stratigraphic interface according to the label changes by post-processing the prediction results. In the following sections, we will present the discussion respectively.

3.1 Data Formulation

There are six features corresponding to each well are given in the form of single point data. These features contains the depth of survey point (Depth), gamma ray (GR), spontaneous potential (SP), acoustic (AC), array induction resistivity (AT90), and array induction resistivity (AT20) that are obtained by different sensors. Each well log data is presented in the form of a single point. The data format of a single well is shown in Table 1.

Table 1. Data format of a single well in dataset.

Wellname	Depth	GR	SP	AC	AT90	AT20	Label
W100	648.000	50.83	40.87	263.05	14.93	15.40	Ja
W100	648.125	53.03	41.73	269.79	13.44	14.54	Ja
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
W100	751.875	84.68	53.91	265.08	17.20	18.04	Jz
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
W100	1807.750	0.00	78.70	237.83	21.47	8.08	c6

Generally, convolutional neural network requires a 2D data as input. At the same time, considering the need to extract all the information of the logging data, we need to convert well logging data points into segment. The continuous data point of the six features within a certain threshold is combined into a two-dimensional segment. And the segment is used as input of CNN model for training process.

We first normalize all data according to the well logging data for the data of a single well with 1 lines of text information. And then we use a window threshold t to slide the window down along the well logging data at intervals of i . Finally, the data of each well in text form is converted into the form of a single-channel segment with a size of $t * 6$. The label corresponding to the segment is the label that appears mostly in the t single-point data selected in each window. The selected label is defined as:

$$label_{pic} = \arg \max(bincount(label[j : j + t])), \tag{1}$$

where $label_{pic}$ is the label corresponding to the segment, and $\arg \max$ is the label index with the largest number. In Eq. 1, the $bincount$ indicates the number of times each label appears, $label$ is the label corresponding to the single point, j is the line j of the text, and j belongs to $0 < j < l - t$. The final number num of segment converted for each well is defined as:

$$num = (l - t + i)/i. \tag{2}$$

In Eq. 2, l is the number of lines in for each well logging data, t is the sliding window size, and i is the sliding interval of the sliding window. The whole process of data formulation is shown in the Fig. 2.

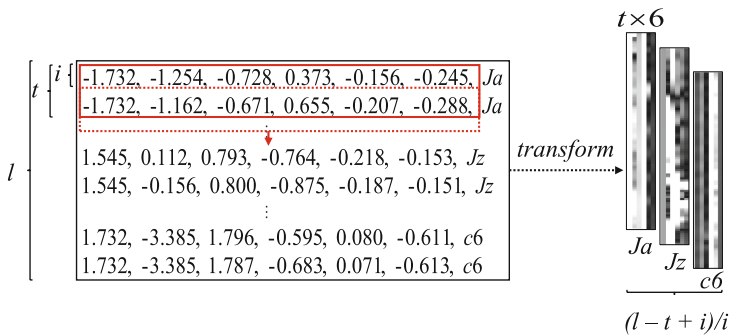


Fig. 2. The process of data formulation.

3.2 Stratigraphy Classification

We formulate the stratigraphic interface detection as a classification problem based on the CNN classification model. The segment obtained as in Sect 3.1

can be used as the input of CNN, and the corresponding label can be used as a specific category of the stratigraphy.

The CNN extracts features from the input segment, and it can obtain a deep feature map through multiple convolution layers. The last fully-connected (FC) layers connect all neurons in the feature maps to perform feature fusion. The output features are used as the input of the multi-class classifier. The proposed CNN model consists of three convolutional layers and two FC layers. The output of the CNN model is a softmax classifier. The details of CNN model structure is summarized in Table 2. During the testing process, the CNN model predict on the basis of segments of the testing well logging data, and output the label corresponding to a single point for each well. The final predicted number of tags for each well num_label is defined as:

$$label_{num} = l - (t - 1), \quad (3)$$

where $label_{num}$ is the number of tags for each well, and t is the sliding window size.

Table 2. The structure of CNN model

Layer	Structure
Input	Size:96 * 6 * 1
Conv1	Kernel size:3 * 3, Filter:64, stride:1, pad:1
Conv2	Kernel size:3 * 3, Filter:128, stride:1, pad:1
Conv3	Kernel size:3 * 3, Filter:256, stride:1, pad:1
FC1	Output number:512
FC2	Output number:512
Output	Softmax,output number:10

3.3 Stratigraphic Interface Detection

We ultimately need to perform stratigraphic interface detection for each well. Therefore, it is necessary to perform a post-processing on basis of the classification results of all the well logging data points.

During the post-processing, we traverse the predicted label $label_predict$. If a label change is detected, we determine whether the label has appeared. On the one hand, if the label has appeared, the label is defined as incorrect and we correct it to the previous label. On the other hand, if the label does not have appeared, we use a threshold $label_step$ at this point and select the label $predict_num$ that appears the most within the threshold. If the two labels are same, the prediction is defined as correct. If they are not same, the label is mispredicted, and the label value is converted to $predict_num$. The algorithm process is shown in Algorithm 1.

After traversing the processed predicted label, if a label change is detected, the depth corresponding to the label is the stratigraphic interface between two adjacent geological layers. The stratigraphic interface detection error can be obtained by comparing the predicted interface with ground-truth.

Algorithm 1. Results post-processing algorithm

```

label_step = 20
label_predict = result[:, -1]
save = []
for label in range(len(set(label_predict)) - 1) do
    predict = []
    save.append(label)
    for i in range(len(label_predict)) do
        if label_predict[i] != label then
            if label_predict[i] in save then
                predict.append(label)
            else
                predict_label_step = np.array(label_predict[i : i + label_step])
                predict_label_step = predict_label_step.astype(np.int)
                predict_num = np.argmax(np.bincount(predict_label_step))
                if label_predict[i] != predict_num then
                    predict.append(label)
                else
                    predict.append(label + 1)
                end if
            end if
        end if
    end for
    else
        predict.append(label)
    end if
end for
end for

```

4 Experiment

4.1 Dataset

We choose a well logging dataset from a real-world oilfield application for stratigraphic interface detection. The dataset contains 3000 wells. The logging data information mainly contains the name of the wells, the geographic location of the wells. Each data point has 6 features, and is associated to a specific stratigraphy label. The dataset contains 10 types of stratigraphy, i.e., ‘K1z’, ‘Jz’, ‘Jy’, ‘Jf’, ‘c1’, ‘c2’, ‘c3’, ‘c4+5’, ‘c6’, and ‘Ja’.

Since the characteristics of wells with similar geographic locations are similar, we selected 228 wells with similar geographic locations according to the coordinate positions as the dataset. The visualization of geographic locations of the whole 3000 well is shown in left part of Fig. 3, and the visualization of

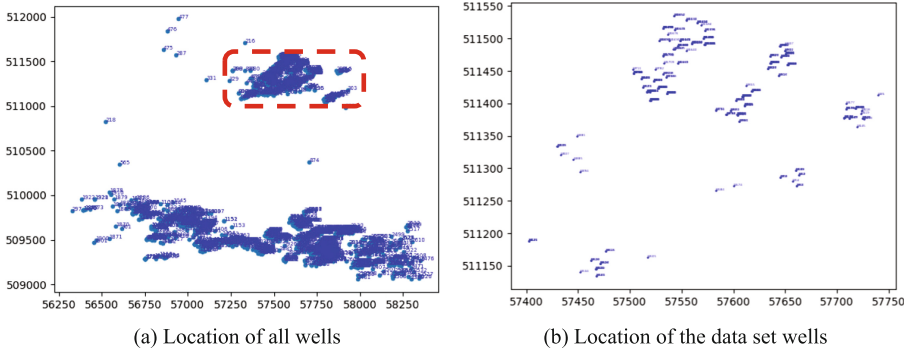


Fig. 3. Select dataset based on coordinates

geographic locations of the selected the 228 wells is shown in the right of Fig. 3. We randomly select 200 wells as the training set from the selected 228 wells, and use left 28 well as the testing set.

In the data formulation process, we set the window threshold as 96 and set the interval as 1. The resulted segments are used as input for the CNN network. During the training phase, we use ‘ReLU’ as the activation functions in the network structure, which can increase the nonlinearity of the network [14, 15]. We use dropout layer [16] with a parameter of 0.5 after each the FC layers. The dropout layer makes each neuron in the CNN activate with a probability of 0.5 to prevent overfitting during the training process.

We employ the strategy of ‘gradual’ learning rate, i.e., the initial learning rate is set as 0.01, and is reduce $9*(1e-6)$ after each epoch. The Adam algorithm [17, 18] is employed to optimize the network during training, and the maximum number of iterations is set to 100. We use the earllystop [19] with a parameter of 6 against overfitting. If the loss rate of the verification set does not decrease for 6 consecutive times as the number of training increases, the training willstop.

4.2 Classification Accuracy

After training, we used the trained CNN model to predict 28 test wells. The final average prediction accuracy is able to achieve 89.69%. The statistical information of the classification of 10 wells is summarized in Table 3. As shown in Table 3, the accuracy and recall rate of the stratigraphy classification are all above 85%, which indicates that the proposed CNN model can show a good effect on the classification for stratigraphic interface detection.

Table 3. The stratigraphy classification accuracy

Wellname	Number	Accuracy	Recall
W1615	12484	0.9350	0.90
W1628	12151	0.9486	0.94
W1669	12490	0.9082	0.89
W1675	12597	0.9472	0.93
W1686	12441	0.8898	0.86
W855	12736	0.9112	0.88
W830	12630	0.9425	0.91
W707	12146	0.8636	0.85
W615	13145	0.9253	0.89
W425	13866	0.9152	0.86

4.3 Stratigraphic Interface Detection

In order to evaluate the stratigraphic interface detection accuracy of 28 testing wells, we adopted the method of calculating the relative error between the predicted detection with ground-truth. The average relative error of the 28 testing is 1%. We summary the maximum, minimum, and average relative error results of the corresponding wells in Table 4. As shown in Table 4, the predicted interface is very close to the ground-truth.

Table 4. The stratigraphic interface detection error

Name	Maximum	Minimum	Average
W1615	0.0446	0.0001	0.0072
W1628	0.0095	0.0003	0.0066
W1669	0.0277	0.0002	0.0089
W1675	0.0333	0.0002	0.0081
W1686	0.0246	0.0008	0.0063
W855	0.0281	0.0004	0.0086
W830	0.0291	0.0002	0.0084
W707	0.0213	0.0001	0.0164
W615	0.0326	0.0002	0.0097
W425	0.0547	0.0003	0.0092

4.4 Time Consumption

We evaluate the time consumption of the CNN model using NVIDIA GeForce RTX 2080 Ti. The training and testing time for the well logging data per well

is shown in the Table 5. From the perspective of the overall training time and the prediction time of a single well, our classification speed is very fast. With the consideration of the classification accuracy and detection error, the time consumption of our proposed approach is able to satisfy real-world application requirements.

Table 5. The time consumption of training and testing phase.

Phase	Criterion	Consumption
Training	Epoch	211 s
	Total	1.6 h
Testing	Well	3.06 s
	Total	85.83 s

4.5 Ablation Study

In order to evaluate the performance of the proposed CNN model, we built MLP network consisting of two FC layers with 512 nodes and a softmax classifier. For MLP training on single-point datas of well logs, the network parameters during the training process are exactly the same as the CNN training process. The each data point with six features is used as input, and the classification result is output through the ‘softmax’ classifier. The details of the MLP model structure is shown in the Table 6.

Table 6. The structure of MLP model

Layer (type)	Structure
Inputlayer	Size:6
FC1	Output number:512
FC2	Output number:512
Output	Softmax, Output number:10

We used the MLP trained model to predict 28 test wells, and the final average prediction accuracy rate was 80%. We summary the prediction accuracy and recall rate of corresponding 10 wells in Table 7. As shown in Table 7 and Table 3, the proposed CNN model greatly improve the stratigraphy classification accuracy and average recall rate. This experiment proved that the construction of the convolutional layer in CNN can extract useful features from the well logging data, and eventually improve the results of stratigraphic interface detection.

Table 7. The classification result of MLP method

Wellname	Number	Accuracy	Recall
W1615	12579	0.8599	0.86
W1628	12246	0.8206	0.82
W1669	12585	0.8525	0.86
W1675	12692	0.8875	0.87
W1686	12536	0.9004	0.88
W855	12831	0.6660	0.64
W830	12725	0.8312	0.82
W707	12241	0.6918	0.72
W615	13240	0.7696	0.75
W425	13961	0.7204	0.66

5 Conclusion

In this paper, we propose a CNN approach for stratigraphic interface detection from the geophysical well logging data. First, the data in the form of a single point of the well logging data is normalized according to the well logging. We then select the sliding window threshold to be 96. We Use the size of 1 as the line interval (0.125 depth interval) along the loggings data sliding window. And we convert data points to 2D segment. The segments are fed into the CNN network as a single-channel picture for training. Secondly, we call the trained model to predict the formation of the test wells. Finally, we introduce a post-processing method to perform the stratigraphic interface detection. The experimental results demonstrate the proposed approach is able to achieve 89.69% of the average accuracy of stratigraphic interface detection. Moreover, the classification accuracy and recall rate of most wells are much higher than the MLP single-point training method. For 200 wells and each well with data of more than 1,500 m, the training phase takes no more than two hours. The forecast duration of a single well is only 3.06 s. In addition, the relative error between the predicted boundary points with the ground-truth is only 1%, which indicates the proposed approach satisfy the real-world application requirements.

The method of interface detection based on CNN proposed in this paper only conducted experiments on division of stratigraphic interface. In the future, this method can be applied to the identification of reservoirs, oil, gas, water and lithology. The biggest advantage of CNN is that through a large amount of data analysis, it can autonomously dig out its inherent characteristics. In addition, we convert single-point well logging data point into segment. Our manner can fully combine the short term temporal information to facilitate subsequent training operations. This provides a brand new method for solving the problems of stratigraphic interface detection, reservoir division and oil, gas and water identification.

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