Multi Classification ERT Flow Pattern Recognition Method Based on Deep Learning

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Abstract. Electrical resistance tomography (ERT) is the frontier technology of modern industrial detection, in which flow pattern is an important index of two-phase flow detection. Affected by many factors, ERT flow pattern recognition is difficult. In this paper, an ERT flow pattern recognition method based on deep learning is designed in order to obtain the real situation of flow pattern in pipeline in practical application. The original ERT measured voltage is transformed from one-dimensional data information to two-dimensional dot matrix information by pseudo image coding method. According to the characteristics, the flow patterns are divided into 27 categories, and then ERT voltage image databases with different scales are established in time domain and frequency domain. Convolutional neural network is used to construct ERT flow pattern recognition network model based on deep learning, and experiments are designed to verify its performance. The results show that the average accuracy of each flow pattern recognition of this algorithm can reach 98.74%, of which the accuracy of 14 types of flow pattern recognition is 100%. This method can achieve high-precision ERT flow pattern recognition task.

1. Introduction
Electrical resistance tomography (ERT) is a visual measurement technology for two-phase or multiphase flow parameter measurement[1], which reconstructs the dielectric conductivity distribution or dielectric constant distribution in the measurement area through boundary measurement values and image reconstruction algorithm[2]. The two-phase flow pattern will affect the flow characteristics and heat and mass transfer performance, and the measurement of other parameters often depends on the accurate identification of convection pattern[3]. Therefore, it is of great significance to study and propose a flow pattern identification method that meets the actual use requirements for solving the two-phase flow problems in petroleum, chemical industry, nuclear industry and other fields[4]. At present, two-phase flow pattern identification methods can be divided into direct measurement identification method and indirect measurement identification method[5-6]. The existing flow pattern recognition methods have many shortcomings. Because the "soft field" characteristics, the number of units in the imaging area, noise, transmission and imaging algorithm will cause the problems of unclear imaging and poor imaging quality in ERT flow pattern reconstruction algorithm, it is difficult to accurately identify the flow pattern category according to the reconstructed image[7].

In recent years, because the in-depth research of deep learning technology has opened up a new way for information acquisition, a variety of mature deep learning frameworks have been widely used in computer vision[8]. In this paper, the deep learning method is applied to flow pattern recognition. Firstly, the pseudo image coding method of ERT measured voltage data is designed. Then, according to the characteristics of ERT flow pattern, it is divided into 27 categories, and the sample databases with
different scales in time domain and frequency domain are constructed. Finally, a convolutional neural network based ERT flow pattern recognition method based on deep learning is designed and verified by comparative experiments.

2. Measurement principle of ERT system
A typical ERT system is shown in figure 1, which mainly includes ERT sensor unit, measurement and data acquisition unit and computer image reconstruction unit. The ERT sensor converts the conductivity distribution information of different media in the measured pipeline into potential signals, then the measurement and data acquisition unit detects the voltage between adjacent electrodes, converts the voltage from analog signals into digital signals, and finally transmits it to the image reconstruction unit (computer) by the communication module[9].

![Figure 1. A typical ERT system](image)

When using ERT system, the excitation current is applied to the electrode array to establish the sensitive field, and measured on different electrodes. The boundary excitation signal is applied to two adjacent electrodes to establish the sensitive field, and the voltage on other adjacent electrode pairs is measured. Then switch to the next adjacent electrode pair for excitation, and measure the voltage on other adjacent and non-excitation electrode pairs. Repeat the above process until all adjacent electrode pairs are excited and all independent measured voltages are detected. For the system with \( N \) electrodes, \( N \cdot (N - 3)/2 \) independent measured voltage data can be obtained by using the adjacent mode, and the field flow pattern distribution information can be obtained by further operation and processing.

3. ERT flow pattern recognition method based on deep learning

3.1. ERT voltage pseudo image coding
The existing ERT flow pattern recognition methods based on deep learning basically take the vector as the input when directly using the measured voltage as the sample. However, the voltage vector is a one-dimensional signal. The feature extraction structure of layer by layer convolution pool in deep learning makes it more sensitive to image information. Therefore, it is not suitable to use deep learning method for feature mining of vector data. Moreover, because the voltage data of different flow patterns measured by ERT system have less intuitive discrimination, if the measured voltage is directly used as a sample, it is difficult to achieve ideal accuracy in identification and reconstruction. Therefore, this paper uses the ERT voltage data processing method shown in figure 2 to convert the one-dimensional voltage signal into two-dimensional image information, that is, pseudo image coding. The processed samples can better meet the advantages of deep learning in image feature extraction, so as to mine the features of different manifolds and complete more detailed classification tasks. On this basis, in order to give full play to the advantages of feature extraction, the samples are transformed in time-frequency domain to find more flow pattern feature information in frequency domain and improve the recognition accuracy.
Using the ERT system with 16 electrode adjacent excitation mode, 208 independent measured values can be measured as described above, and the measured voltage is the voltage value of 208 * 1 dimension. Set the total number of database samples as group $P$. The specific steps of ERT voltage data processing are as follows: normalize the measured voltage with group $P$ dimension of 208 * 1 so that its value is between 0 and 1

$$u_k(i) = \frac{x_k(i) - \min[x_k(i)]}{\max[x_k(i)] - \min[x_k(i)]}$$

$$k = 1, 2, 3, ..., P; i = 1, 2, 3, ..., 208$$

The normalized measured voltage $U$ is upgraded to obtain a 208 * 208 voltage matrix

$$U_k = u_k u_k^T$$

Fill the edges of $P$ voltage matrices $U_k$ with zeros to expand the dimension to 256 * 256, and then multiply each element value by 255 to obtain $P$ matrices with element values within 0 ~ 255

$$U_k = \begin{pmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{k1} & \cdots & u_{kk} \end{pmatrix} \rightarrow H_k = 255 * \begin{pmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \\ u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{k1} & \cdots & u_{kk} \end{pmatrix}$$

At this time, the obtained matrix can be regarded as the pixel value matrix corresponding to the dot matrix image of 256 * 256 * 1. It is converted into JPG format image and becomes $P$ dot matrix images containing measured voltage information. The dot matrix image is transformed by DCT to enhance its characteristics [26], and the DCT voltage samples are obtained.

3.2. CNN flow pattern identification model

The CNN structure built in this paper can be divided into four parts: input layer, feature extraction layer, full connection layer and output layer. The input layer acts directly on the input data (pixel value of the image). The input sample of the network is the voltage lattice obtained after processing the measured voltage in the database, with the size of 256 * 256.
The feature extraction layer consists of two parts. The first part is the convolution layer, which is mainly used to extract the characteristics of input data, and its input comes from the input layer or pooling layer. Each characteristic graph in the convolution layer has a corresponding convolution kernel, which is the same size as the convolution kernel. Different convolution kernels first do convolution on the feature map input from the previous layer, add a bias after accumulating the corresponding elements, and then operate through the activation function to obtain the feature map.

The model designed in this paper adopts two-layer convolution and two-layer pooling. The size of convolution kernels is 5 * 5 and the number is 20. The pool layer pool area selects the maximum pool, with a size of 2 * 2, in order to retain the image texture information. The RELU activation function is introduced to improve the network expression ability. The full connection layer contains 27 neurons, and the learned “distributed feature representation” is mapped to the sample marker space. The output layer uses softmax function, which is a “Classifier”. It can be divided into two stages: soft and max. After the input neuron \( z_j \) is mapped to a value on (0, 1), \( f(z) \) is used to calculate the classification probability of each neuron, so as to complete the flow pattern recognition.

\[
f(z_j) = \frac{e^{z_j}}{\sum_{j=1}^{n} e^{z_j}}, \quad \sum_{j=1}^{n} f(z_j) = 1
\]

4. Experimental results and analysis

4.1. Build ERT database

In this paper, the experimental data of ERT reconstructed images are established by finite element simulation method. The specific simulation conditions are as follows: 16 electrode system; Adjacent excitation mode (excitation current 10mA); 100mm pipe diameter is divided into 1024 units (1024 pixels); Continuous phase medium (tap water) with conductivity of 0.02s/m and dispersed phase medium (air) with conductivity of 0s / m. In the existing flow pattern identification methods, most of the flow patterns are divided into core flow, bubble flow, circulation and laminar flow. Set the imaging area of ERT system (diameter d). According to the characteristics of different flow patterns, ERT flow patterns are divided into 27 categories. See table 1 for specific classification basis.
Table 1. Basis of ERT flow pattern classification

| Number | Category          | Feature description                           | Set area | Sample |
|--------|-------------------|-----------------------------------------------|----------|--------|
| 1      | Core flow         | In the center                                |          |        |
|        |                   | Approximately circular                        |          |        |
| 2      | One bubble-1      | In the first quadrant                         |          |        |
| 6      | Two bubbles-11    | All in the first quadrant                     |          |        |
| 10     | Two bubbles-11    | Located in the first and second quadrants respectively |        |        |
| 16     | Three bubbles - 123 | Located in the first, second and third quadrants respectively |        |        |
| 20     | Four bubbles      | Random distribution                           |          |        |
| 21     | Five bubbles      | Random distribution                           |          |        |
| 23     | Middle ring flow  | Diameter of the inner and outer ring of the ring is between 1 / 3D and 2 / 3D |        |        |
| 26     | Median laminar flow | Layer height is between 1 / 3D and 2 / 3D     |          |        |

The ERT image voltage database constructed according to the classification basis is used for training and testing (27 categories, including 100 groups of data in each category). Each group of data includes measured voltage (208 * 1), voltage dot matrix (256 * 256), DCT voltage sample (256 * 256), quarter down sampling voltage dot matrix (64 * 64), quarter down sampling DCT voltage sample (64 * 64), initial flow pattern setting image and Newton Raphson algorithm reconstruction image (256 * 256). Each class of the data set is randomly divided into training samples and test samples. Each class of flow pattern training and test samples account for 90% and 10%.

4.2. Experimental results and comparison of different methods

Hardware environment: CPU is Intel(R) Core(TM) i9-9900X CPU@3.50GHz 3.50GHz, GPU is NVIDIA GeForce RTX 2080 Ti. Software environment: Windows 10, RAM 32GB. This experiment uses Python 3.5.3 to build the algorithm model under the framework of tensorflow-gpu1.8.0.
In order to prove the performance and superiority of the flow pattern recognition model based on convolution neural network designed in this paper, four classical classification algorithms of SVM (Experiment 1), Bayesian (Experiment 2), KNN (Experiment 3) and BP (Experiment 4) neural network are used for comparative experiments. The experimental samples are processed voltage lattice and corresponding DCT voltage samples. In addition, in order to prove the effectiveness of the data processing method used in this paper, Experiment 5 and Experiment 6 are designed. In Experiment 5, the image reconstructed by Newton Raphson algorithm is trained as the input of convolutional neural network in the database; In Experiment 6, the existing ERT flow pattern recognition network based on LSTM is used, and the unprocessed original measured voltage is used as the input sample for training and recognition. The comparison results of experimental accuracy are shown in table 2.

| Table 2. Accuracy of each flow pattern recognition algorithm |
|------------------------------------------------------------|
| The algorithm in this paper | SVM | Bayes | KNN | BP | CNN | LSTM |
| 256*256 | 64*64 |          |      |     |     |      |
| Core flow | 100 | 100 | 100 | 83 | 98 | 87 | 100 | 73 |
| One bubble-1 | 98 | 96 | 81 | 85 | 77 | 90 | 90 | 66 |
| One bubble-2 | 98 | 95 | 68 | 83 | 74 | 91 | 88 | 78 |
| One bubble-3 | 97 | 98 | 79 | 78 | 79 | 84 | 85 | 62 |
| One bubble-4 | 97 | 98 | 79 | 78 | 79 | 84 | 85 | 76 |
| Two bubbles-11 | 98 | 97 | 84 | 76 | 82 | 79 | 86 | 72 |
| Two bubbles-22 | 97 | 96 | 91 | 73 | 79 | 76 | 80 | 66 |
| Two bubbles-33 | 96 | 98 | 88 | 82 | 75 | 70 | 83 | 72 |
| Two bubbles-44 | 98 | 97 | 90 | 70 | 80 | 73 | 78 | 61 |
| Two bubbles-12 | 100 | 100 | 97 | 89 | 94 | 100 | 98 | 94 |
| Two bubbles-13 | 100 | 100 | 99 | 91 | 97 | 98 | 96 | 78 |
| Two bubbles-14 | 100 | 100 | 99 | 85 | 97 | 100 | 97 | 81 |
| Two bubbles-23 | 100 | 100 | 98 | 87 | 93 | 100 | 97 | 74 |
| Two bubbles-24 | 100 | 100 | 98 | 83 | 95 | 99 | 95 | 89 |
| Two bubbles-34 | 100 | 100 | 100 | 87 | 94 | 100 | 92 | 91 |
| Three bubbles-123 | 100 | 100 | 96 | 76 | 99 | 100 | 93 | 94 |
| Three bubbles-124 | 100 | 100 | 96 | 87 | 100 | 97 | 97 | 91 |
| Three bubbles-134 | 100 | 100 | 100 | 78 | 98 | 93 | 95 | 88 |
| Three bubbles-234 | 100 | 100 | 100 | 82 | 99 | 100 | 94 | 92 |
| Four bubbles | 96 | 96 | 87 | 75 | 80 | 81 | 82 | 79 |
| Five bubbles | 96 | 94 | 91 | 83 | 83 | 85 | 87 | 68 |
| Small annular flow | 100 | 100 | 100 | 82 | 100 | 81 | 94 | 86 |
| Middle ring flow | 100 | 100 | 100 | 87 | 97 | 99 | 100 | 89 |
| Large circulation | 99 | 95 | 99 | 91 | 99 | 99 | 99 | 75 |
| Low level laminar flow | 100 | 100 | 100 | 97 | 100 | 100 | 98 | 76 |
| Median laminar flow | 97 | 99 | 88 | 98 | 96 | 99 | 94 | 80 |
| High level laminar flow | 99 | 97 | 94 | 79 | 97 | 95 | 97 | 94 |

The experimental results shown in table 2 show that the ERT flow pattern recognition model based on CNN designed in this paper can obtain high accuracy in identifying various flow patterns. The recognition accuracy of each flow pattern can reach more than 95%, and the recognition accuracy of 14 types of flow patterns is 100%. From the results of Comparative Experiments 1 to 4, it can be seen that the flow pattern recognition method in this paper has higher accuracy than the flow pattern recognition model based on SVM, Bayesian, KNN and BP. Comparing experiments 5 and 6, it can be seen that after using the processing method involved in this paper to process voltage data, it can still achieve high accuracy in identifying easily confused flow patterns, which has obvious advantages.
Figure 4 shows the fitting results of the accuracy of each method when the ideal accuracy of each type of flow pattern recognition is set to 100%. It can be seen more intuitively that the accuracy of the model designed in this paper is significantly higher than that of other methods. In conclusion, the ERT flow pattern recognition method based on convolutional neural network designed in this paper can better complete the recognition task and has high accuracy.

5. Conclusion
This paper presents an ERT flow pattern recognition method based on deep learning. A pseudo image coding method is used to transform the one-dimensional voltage data information into two-dimensional lattice information, so as to ensure the integrity of the original data and enhance the data characteristics. According to the flow pattern characteristics, the ERT voltage image database with multi-scale and multi flow pattern classification under dual channels in time domain and frequency domain, original scale and quarter down sampling is constructed. Convolutional neural network is used to build ERT flow pattern recognition method model based on deep learning. The experimental results show that the average accuracy of each flow pattern recognition is more than 98.74%, and the accuracy of 14 types of flow patterns is 100%. It can realize high accuracy flow pattern recognition, has advantages in identifying easily confused flow patterns, solves the problems of existing methods to a certain extent, and greatly improves the recognition accuracy of multi classification flow patterns.

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