

Design of a Machine Learning-Based Electrical Resistance Tomography System

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Abstract: To address the issues of high computational complexity and poor real-time performance of traditional inversion methods in electrical resistance tomography (ERT), which make it difficult to meet the high-precision detection requirements of industrial two-phase flow, this paper proposes a machine learning-based approach for reconstructing conductivity distribution in ERT. A dataset containing 10,000 single-target and dual-target samples is constructed via simulations on the EIDORS platform. Three models with different methodological principles — extreme learning machine (ELM), ridge regression, and random forest — are selected for comparative experiments. The imaging quality is evaluated using root mean square error (RMSE) and image correlation coefficient (ICC). Experimental results show that ELM achieves the best performance on both single-target and dual-target test sets, with RMSE values of 0.0353 and 0.0374, respectively, significantly outperforming the other two models. This method effectively alleviates the ill-posedness of the ERT inverse problem and provides a feasible solution for high-precision real-time imaging in industrial two-phase flow.

Keywords: Electrical resistance tomography ; Machine learning ; Conductivity reconstruction ; Extreme learning machine ; Two-phase flow

1. INTRODUCTION

Process tomography injects excitation signals into the measured field domain through a sensor array, collects boundary response information, and then uses inversion algorithms to solve the spatial distribution of physical parameters inside the field domain. Finally, it visualizes the field state in a graphical form. With the significant advantages of non-intrusive measurement, fast real-time response and wide applicability across scenarios, it has been widely applied in industrial, medical and other fields^[1]. Electrical tomography, as an important branch of process tomography, uses electrical signals as excitation and reconstructs the internal parameter distribution by detecting the electrical response at the field boundary. Among them, Electrical Capacitance Tomography (ECT) measures permittivity, and Electrical Resistance Tomography (ERT) measures electrical conductivity. The fused imaging method of the two can simultaneously obtain the distribution information of both parameters, further enriching the characterization dimension of the field state.

Electrical Resistance Tomography (ERT) has become the core development direction in the field of two-phase flow detection due to its advantages of low cost, fast response, high safety and wide applicability. Its application in flow pattern identification and image reconstruction of two-phase flow media in closed vessels^[2] is a key issue in practical industrial implementation. Two-phase flow detection technology has irreplaceable application value in modern engineering fields such as energy and power, process industry, and aerospace. With the rapid development of petroleum, chemical, metallurgical and other industries, two-phase flow pipeline transportation systems are increasingly widely used. Parameters such as phase fraction and flow pattern inside the pipeline directly affect transportation safety and efficiency, making scientific and accurate online monitoring an urgent demand in engineering practice.

To address the above dual bottlenecks, machine learning methods have been introduced into ERT image reconstruction and parameter inversion research in recent years. Centered on

data-driven paradigm, these methods can directly learn the complex nonlinear mapping relationship between boundary voltage signals and field conductivity distribution from a large number of measurement data. They avoid the drawbacks of traditional inversion methods, including tedious iterative computation, high difficulty in physical modeling, sensitivity to initial values and tendency to fall into local optima. This provides a new solution for the low-cost and real-time engineering application of ERT technology, and has also become a research hotspot in the fields of process tomography and two-phase flow detection^[3].

2. RESEARCH FRAMEWORK

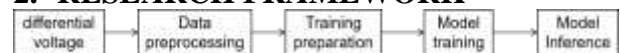


Figure 1 Methodological framework of the study

Research on conductivity distribution prediction based on Electrical Resistance Tomography (ERT) mainly consists of four core stages: data preprocessing, training preparation, model training, and model inference. The overall workflow framework is illustrated in Figure 1. First, boundary voltage data of the target field domain are collected through the ERT sensor array. Subsequently, preprocessing is performed on the raw voltage data, including normalization, denoising, and effective feature extraction. Then, training preparation is carried out, where the dataset is divided into a training set and a test set, and the input-output data format conforming to the model requirements is constructed. After that, the model training stage is entered, in which machine learning algorithms are used to learn the mapping relationship between boundary voltage signals and field conductivity distributions. Finally, model inference is completed to realize rapid reconstruction of conductivity distribution from newly collected voltage data.

2.1 Machine Learning Models

Machine learning methods can be mainly divided into three categories according to task types: regression prediction, classification prediction, and time series prediction. In this paper, predicting the internal conductivity distribution of the field domain and two-phase flow characteristic parameters

using machine learning models based on the Electrical Resistance Tomography (ERT) two-phase flow system dataset belongs to the multivariate regression prediction problem. In addition, dataset characteristics are crucial for the selection of machine learning models, and dataset size, data type, and data structure are all key influencing factors. The ERT dataset used in this study takes 208-dimensional boundary voltage measurements as input features and 576-dimensional field conductivity distribution values as output targets. This high-dimensional input-high-dimensional output strongly nonlinear mapping relationship puts forward higher requirements for model architecture design. Considering the type of research problem, dataset characteristics, and the dual requirements of real-time performance and accuracy in practical applications, this paper selects three machine learning models with different technical paths for comparative research: Extreme Learning Machine (ELM), Ridge Regression, and Random Forest (RF).

(1) Extreme Learning Machine (ELM) is a fast learning algorithm for single-hidden layer feedforward neural networks [4]. Its core feature is that the connection weights and biases from the input layer to the hidden layer are randomly initialized, and the output layer weights are only solved analytically by the least squares method. This algorithm has the significant advantages of fast training speed and good generalization performance, which can meet the core real-time requirements of Electrical Resistance Tomography (ERT) systems.

(2) Ridge Regression is a linear regression algorithm with L2 norm regularization constraint. Based on the ordinary least squares method, it introduces a penalty term of the sum of squared weights and directly obtains the globally optimal model parameters by solving the closed-form solution [5]. This algorithm can effectively suppress overfitting and has excellent numerical stability, which can alleviate the severe ill-posedness of the ERT inverse problem to a certain extent.

(3) Random Forest (RF) is an ensemble learning algorithm based on the Bagging framework [6]. It generates multiple independent decision trees by randomly sampling samples and features, and finally outputs the regression results using an averaging mechanism. It not only significantly reduces the overfitting risk of a single decision tree and adapts to the modeling requirements of high-dimensional input data, but also can output the feature importance ranking of each input electrode voltage signal, providing support for the physical interpretability of ERT imaging.

2.2 Data Acquisition and Correlation Analysis

The training process of machine learning models relies on large-scale datasets, and the generalization ability of the models largely depends on the quality of the dataset. However, in practical engineering scenarios, it is extremely costly and difficult to collect a large number of labeled samples through physical ERT systems. Therefore, this paper adopts the finite element forward modeling program of the EIDORS open-source platform to construct a simulated ERT system for generating standardized datasets. The forward program discretizes the circular target field domain into 576 finite element units. The simulation system mimics a 16-electrode ERT device in a pipeline, adopting the adjacent-adjacent (ad-ad) excitation and measurement mode, i.e., injecting current through adjacent electrodes and collecting voltage from adjacent electrodes.

The simulation parameters are set as follows: the diameter of the circular pipeline $D=0.2$ m; the background solution

simulates the liquid phase in the pipeline with a conductivity of 10^{-3} S/m; the circular anomalies simulate the gas phase in the pipeline with a uniform diameter $d=0.02$ m and a conductivity of 0 S/m. This paper designs simulation scenarios with 1, 2 circular anomalies, and finally selects 5000 groups of samples for each of the 1-anomaly and 2-anomaly scenarios, totaling 10000 valid data samples. The schematic diagram of partial dataset samples is shown in Figure 2.

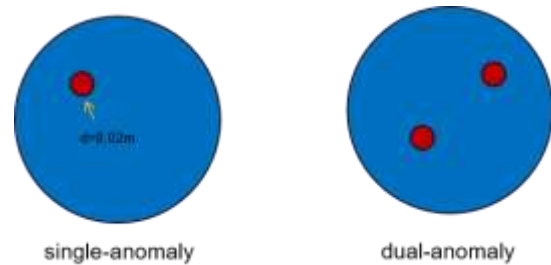


Figure 2 Selected Samples of ERT Two-Phase Flow Dataset

Each group of data contains the conductivity distribution values of 576 field units and the corresponding 208 boundary voltage measurements. All data are normalized, and the conductivity data and voltage measurements are normalized to the interval $[0,1]$ through equations(2-1) and (2-2), respectively.

$$U_i = \frac{U_i - U_{\min}}{U_{\max} - U_{\min}} \quad (2-1)$$

$$\sigma_i = \frac{\sigma_i - \sigma_{\min}}{\sigma_{\max} - \sigma_{\min}} \quad (2-2)$$

2.3 Data preprocessing

Selecting appropriate input parameters is crucial for constructing a high-performance phase holdup prediction model for two-phase flow in ERT pipelines. In this paper, the boundary voltage measurements from each independent electrode pair (208 in total) are selected as input variables to exploit the complete electric field distribution information captured by the ERT system. The output of the model is the spatial distribution of conductivity in the target cross-section, which is reconstructed from boundary voltages to internal physical property fields by solving a parameter field consisting of 576 finite element units. To accelerate model convergence, avoid numerical instability, and ensure equal weighting of features, the input and output variables in the dataset are normalized to the interval $[0, 1]$. Finally, all data are randomly shuffled to improve the generalization ability of the model, and the dataset is divided into training and test sets with a ratio of 9000:1000. The training set is used for parameter tuning, training, and cross-validation, while the test set is used to evaluate the predictive performance of the trained model.

3. EXPERIMENT AND RESULT ANALYSIS

3.1 Experimental Settings

3.1.1 Experimental Parameter Setting

The experimental environment is Windows 10 64-bit, with an AMD Ryzen 5 processor and 8 GB of RAM, implemented in MATLAB R2024a.

3.1.2 Comparative Models

In this study, three typical supervised learning algorithms — extreme learning machine (ELM), ridge regression, and random forest — are selected for comparative experiments. These three types of algorithms correspond to three distinct machine learning approaches: fast feedforward neural networks,

linear regularized regression, and ensemble learning, respectively. The aim is to comprehensively evaluate the applicability of different methods to the task of conductivity distribution reconstruction in electrical resistance tomography (ERT). The main parameter settings of each algorithm are listed in Table 1.

Table 1 Selection and Value Determination of ML Model Hyperparameters

Algorithm	Main parameters
ELM	Hidden layer nodes: 550
Ridge	Regularization parameter: 0.001
RF	Number of trees: 100, Minimum samples per leaf: 5

3.1.3 Evaluation Metrics

To compare the image reconstruction quality of different algorithms for the ERT system, the root mean square error (RMSE) and the image correlation coefficient (ICC) are selected as the evaluation metrics [7]. Equations (3-1) and (3-2) present the calculation methods for RMSE and ICC, respectively. RMSE is a commonly used performance metric in regression problems. It computes the root mean square difference between the predicted values and the true values, reflecting the overall magnitude of the deviation, with greater sensitivity to large errors. In this study, RMSE is adopted to evaluate the prediction accuracy of different algorithms. Regarding image reconstruction quality, an RMSE value closer to 0 indicates that the reconstructed image is closer to the true conductivity distribution, implying better imaging quality; conversely, a larger RMSE value suggests a greater deviation from the actual distribution and poorer imaging quality.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (R_i - Y_i)^2} \quad (3-1)$$

ICC is a statistical metric for image similarity that measures the correlation between the predicted image and the true image, and is one of the commonly used evaluation metrics for image reconstruction algorithms. In this study, it is necessary to evaluate the correlation between the imaging results of the algorithms and the actual images; therefore, ICC is adopted as the evaluation metric. Regarding image reconstruction quality, an ICC value closer to 1 indicates that the reconstructed image is closer to the true distribution, implying better imaging quality; conversely, an ICC value closer to 0 suggests a larger deviation from the actual distribution and poorer imaging quality.

$$ICC = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(R_i - \bar{R})}{\sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2 \sum_{i=1}^n (R_i - \bar{R})^2}} \quad (3-2)$$

In Equations (3-1) and (3-2), Y_i and \bar{Y} denote the predicted conductivity and its mean value, respectively; R_i and \bar{R} denote the true conductivity and its mean value, respectively; and n is the number of divided elements.

3.2 Experimental Results and Analysis

3.2.1 Comparative Experiments

In this experiment, three different algorithms—extreme learning machine, ridge regression, and random forest—are selected for comparison. During model training, all three models are evaluated based on the same test set, and the final experimental results are shown in Table 2 and Table 4.

Table 2 Single-target true distribution and image reconstruction results

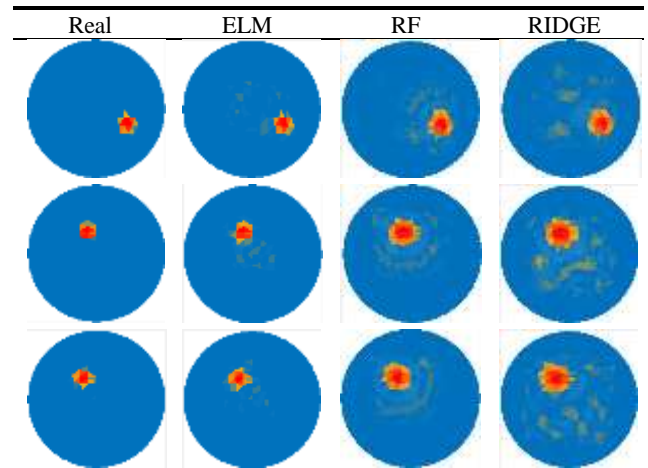
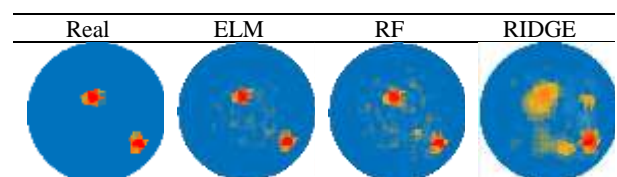


Table 3 Mean RMSE and ICC on the single-target test set

Algorithm name	Average RMSE	Average ICC
ELM	0.0353	0.9532
RF	0.0533	0.8641
RIDGE	0.0679	0.8035

The results on the single-target test set show that, in the electrical resistance tomography (ERT) reconstruction task, the extreme learning machine (ELM) achieves the best overall performance. Its average root mean square error (RMSE) on the test set is as low as 0.0353, and the image correlation coefficient (ICC) is as high as 0.9532, indicating the lowest reconstruction error and the strongest agreement between the predicted results and the true values among all compared algorithms. Compared with the linearly regularized ridge regression (RIDGE) algorithm, ELM reduces the reconstruction error (RMSE) by 48.0% and improves the consistency metric (ICC) by 18.6%. Compared with the ensemble learning random forest (RF) algorithm, ELM reduces the RMSE by 33.8% and improves the ICC by 10.3%. These results fully demonstrate that the performance of the ELM algorithm in the ERT reconstruction task is significantly superior to both the linear baseline model RIDGE and the ensemble learning model RF. Its strong nonlinear mapping capability and excellent generalization robustness can effectively alleviate the ill-posedness of the ERT inverse problem, making it more suitable for high-precision and real-time imaging reconstruction requirements in engineering scenarios.

Table 4 Dual-target true distribution and image reconstruction results



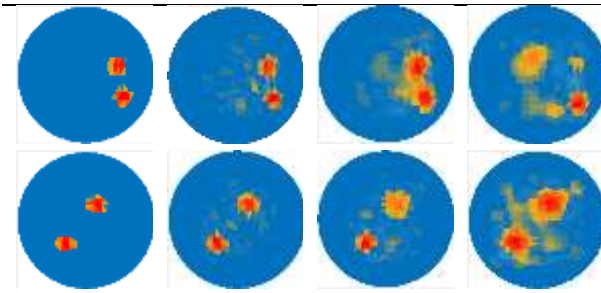


Table 5 Mean RMSE and ICC on the dual-target test set

Algorithm name	Average RMSE	Average ICC
ELM	0.0374	0.8071
RF	0.0655	0.7234
RIDGE	0.0783	0.6786

The results on the dual-target test set shown in the table indicate that, in the more challenging electrical resistance tomography (ERT) dual-target reconstruction task — where there are more anomalies, the ill-posedness of the inverse problem is stronger, and the reconstruction difficulty is higher — the extreme learning machine (ELM) still achieves the best overall performance. Its average root mean square error (RMSE) on the test set is as low as 0.0374, and the image correlation coefficient (ICC) is as high as 0.8071, representing the lowest reconstruction error and the strongest agreement between the predicted conductivity distribution and the true field among the three compared algorithms, thereby demonstrating excellent multi-target nonlinear mapping capability. Compared with the linearly regularized ridge regression (RIDGE) algorithm, ELM reduces the reconstruction error (RMSE) by 52.2% and improves the consistency metric (ICC) by 18.9%. Compared with the ensemble learning random forest (RF) algorithm, ELM reduces the RMSE by 42.9% and improves the ICC by 11.6%. These results fully demonstrate that, compared with the linear baseline model RIDGE and the ensemble learning model RF, the ELM algorithm exhibits more prominent performance advantages in solving the high-complexity inverse problem of multi-target reconstruction. Its fast learning characteristic and strong generalization robustness make it well-suited for high-precision and real-time ERT reconstruction requirements in scenarios with multiple anomalous targets.

3.3 Analysis of Model Rationality and Interpretability

3.3.1 Model Rationality

In terms of model type coverage, the three models (ELM, RF, Ridge) cover ensemble learning, fast neural networks, and linear regularized regression, enabling a comprehensive evaluation for ERT parameter reconstruction. ELM suits real-time ERT imaging due to its fast training and strong nonlinear fitting. RF assesses feature importance of measurement signals, helping identify key channels. Ridge suppresses overfitting under ill-posed conditions, providing a stable baseline. Considering data scale and computational cost, all three models require moderate resources and achieve high efficiency on the ERT dataset. ELM and Ridge are fast and easy to tune. RF involves slightly higher computation but still runs efficiently on conventional platforms, meeting low-cost, easy-deployment needs for ERT systems.

More complex models (XGBoost, LightGBM, Transformer) are not used because: RF already represents bagging-based ensemble learning; Boosting models (e.g., XGBoost) are more time-consuming, harder to tune, and prone to overfitting on current data. Advanced ensembles and deep learning models rely on larger data and stronger compute, often causing redundancy and overfitting on typical ERT datasets, with high deployment barriers. Our core goal is an efficient, stable, easily implementable ERT method. The three selected models—Ridge, ELM, RF—cover linear baseline, fast nonlinear learning, and bagging ensemble, enabling thorough comparison and selection of the optimal model for ERT.

3.3.2 Model Interpretability

(1) Random Forest:

RF is based on the ensemble learning mechanism of multiple decision trees. Its core interpretability advantage lies in its ability to directly output the relative importance ranking of the voltage measurement signals from each input electrode with respect to the conductivity distribution reconstruction result. This ranking essentially reflects the differences in information contribution of different measurement channels in solving the inverse problem of electrical resistance tomography (ERT), and can directly correspond to the sensitivity field distribution theory of ERT.

(2) Ridge Regression:

Ridge regression is based on a linear regression mechanism with L2 regularization. Its interpretability is reflected in the fact that the regression coefficients directly indicate the linear contribution of each input electrode voltage signal to the conductivity distribution reconstruction result. However, this purely linear mapping capability cannot capture the strong nonlinear correlations in the ERT inverse problem, resulting in reconstruction accuracy and generalization performance far inferior to those of nonlinear machine learning algorithms.

(3) Extreme Learning Machine:

Due to its characteristic of "randomly initializing input-to-hidden layer weights and only optimizing the output layer weights", the interpretability of ELM is slightly weaker than that of BP neural networks. Nevertheless, the prediction logic can still be traced through the contribution analysis of hidden layer nodes. The node contribution is calculated as "hidden layer output value \times output layer weight", reflecting the role of each hidden layer node in the final prediction. The source of the node contribution can then be associated with specific combinations of input parameters.

4. SUMMARY

To improve the image reconstruction quality of electrical resistance tomography (ERT), this paper selects three typical machine learning models — extreme learning machine (ELM), ridge regression (Ridge), and random forest (RF) — for a comparative study. Among them, ELM achieves extremely fast training speed and strong nonlinear fitting capability by randomly initializing input weights and analytically computing output weights. Ridge adopts L2-regularized linear regression to suppress overfitting under ill-posed inverse problems. RF, based on the ensemble learning mechanism of multiple decision trees, can evaluate the feature importance of different measurement channels. Experimental results show that all three models effectively enhance the reconstruction accuracy of ERT, among which ELM achieves the best overall performance. On the single-target and dual-target test sets, the average root mean square error (RMSE) of ELM is as low as 0.0353 and 0.0374, respectively, and the image correlation coefficient (ICC) reaches as high as 0.9532 and 0.8071, respectively,

significantly outperforming Ridge and RF. Therefore, with its fast learning capability and strong generalization robustness, ELM is more suitable for high-precision real-time imaging requirements in industrial two-phase flow.

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