Inversion of Two-dimensional Electrical Resistivity data using Convolutional Neural Networks (U-Net)

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Abstract

The interpretation of ERT data requires inversion, which is challenging due to its nonlinear and illposed nature. We aim to solve the inverse problem using a machine learning technique that approximates the complex non-linearity using the data provided without specifying any geophysical or mathematical equations. Specifically, we make use of CNN with U-Net architecture to estimate the true subsurface resistivity model from observed apparent resistivity data (pseudosection). U-Net is selected because it works well when both input and output data are in the form of images, and in the present work, input (pseudosection) and output (subsurface resistivity model) have spatial correspondence and existing local patterns.

For ERT inversion, U-Net learns by minimizing pixel mean squared error between the true and predicted subsurface resistivity images. The ERT dataset was generated by simulating a dipoledipole survey over a 400m x 100m earth containing two anomalous blocks with varying resistivity, size, and position in a variable homogeneous background resistivity. We used a finite element approach with a triangular mesh grid for forward modelling (using pyGIMLi) and added Gaussian noise to the calculated pseudosection so that simulated data resembles the field data.

The U-Net model was trained on 4000 samples (20% of training samples used for validation) and tested on 1000 samples. The architecture consisted of an encoder and decoder subnetwork connected by a bridge section. The encoder depth was 7, and each block in the encoder subnetwork consisted of two sets of convolutional and ReLU layers, followed by a max pooling layer. The decoder subnetwork consisted of a transposed convolution layer for upsampling, followed by two sets of convolutional and ReLU layers. The weights of all the convolutional layers were initialized using the He Normal initializer. We used Adam optimizer with a learning rate of 0.0001. The U-Net model was allowed to train for 100 epochs with a batch size of 128. The trained U-Net model gave good predictions of the anomalous blocks and background resistivity with a root mean square misfit of 2.86% on test data and 2% on training data. The results confirm the efficacy and effectiveness of the proposed U-Net architecture in predicting the subsurface resistivity variation from the DC resistivity data.

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PRESENTED AT:

INTRODUCTION

Electrical resistivity tomography (ERT) is a geophysical method used to image the subsurface by interpreting apparent resistivity data calculated from measurements of potential difference over an arrangement of electrodes at the surface.

ERT has found application in various domains like environmental assessment, archaeological surveys, mineralogical studies and hydrogeological mapping.

It is based on solving Poisson's equation for the electrical potential.

The interpretation of ERT data requires performing inversion, which is challenging due to its nonlinear and ill-posed nature.

The suboptimal approximation and need for an accurate initial model make conventional inversion schemes less popular.

We aim to solve the inverse problem using a machine learning technique that can approximate the complex non-linearity using the data provided without specifying any geophysical or mathematical equations.

Specifically, we use Convolutional Neural Networks (CNN) with U-Net architecture (Ronneberger et al., 2015) to estimate the true subsurface resistivity model from an observed apparent resistivity pseudosection.

U-Net is selected because of its effectiveness when both input and output data are images. In the case of ERT, input (apparent resistivity pseudosection) and output (subsurface resistivity distribution) have spatial correspondence and existing local patterns.

METHODOLOGY

The apparent resistivity data (pseudosection) acts as input to the convolutional neural network (U-Net) that outputs the true subsurface resistivity distribution.

U-Net learns by minimizing the pixel-by-pixel mean squared error between the true and predicted subsurface resistivity images.

The first step is image dataset generation (forward simulation), followed by inversion using CNN.

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Workflow: Data generation followed by inversion using CNN

FORWARD SIMULATION AND DATA GENERATION

The forward operator that links the resistivity of the subsurface with apparent resistivity data calculated from the potential difference measurements is given by-

$$\nabla.\left(-\frac{1}{\rho}\nabla\Phi\right) = I_0[\delta(r-r^+) - \delta(r-r^-)]$$

Where ρ (Ωm) depicts the electrical resistivity, ϕ (V) is the electric potential at location r as a result of current injected I_o(A) between two electrodes located at r− and r+, and δ is the Dirac Distribution.

The apparent resistivity ρ_a is calculated from the measured voltage data using,

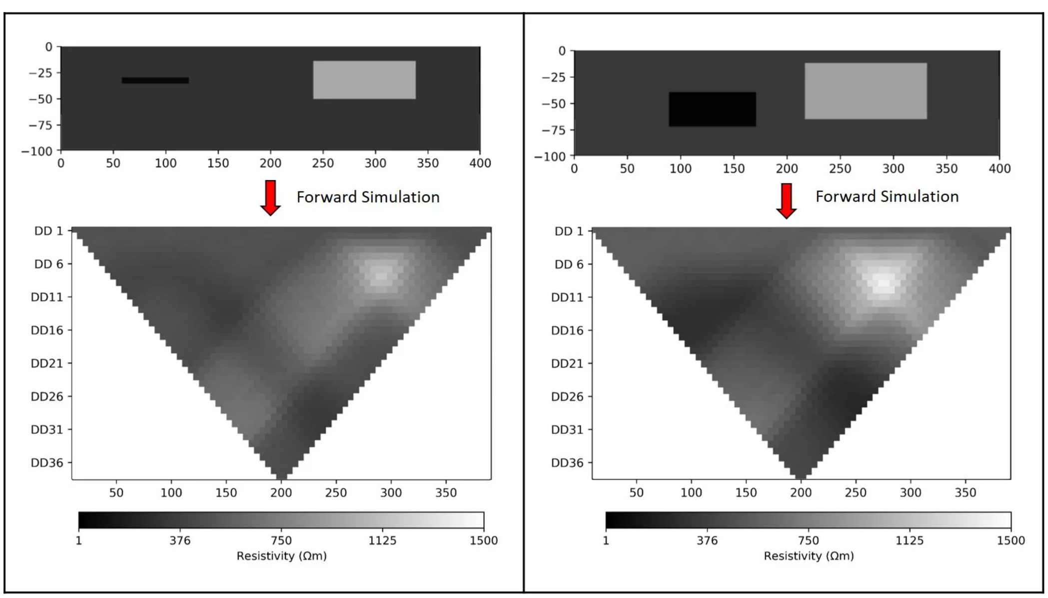
$$\rho_a = k\frac{\Delta V}{I_0}$$

A finite element-based approach was used to solve the above equations on a triangular mesh grid using PyGimLi (Rucker et al., 2017).

The dataset was generated by simulating a dipole-dipole ERT survey over 400m x 100m earth models with 10m electrode spacing.

The earth models consisted of a conductive and resistive block with varying dimensions, resistivity values, and positions.

Gaussian noise was added to the calculated apparent resistivity pseudosections so that simulated data resembles the field data.



Forward simulation using finite element approach

CNN ARCHITECTURE, TRAINING AND INVERSION

The CNN (U-Net) architecture consists of two subnetworks. The first half is an encoder (contraction path for downsampling) and the second half is a decoder (expansion path for upsampling) connected by a bridge section (centre block).

The encoder depth in our U-Net architecture is seven.

[VIDEO] https://res.cloudinary.com/amuze-interactive/image/upload/f_auto,q_auto/v1670257296/agu%20fm2022/0d-cf-27-1c-14-9e-73-0c-21-1e-fa-05-2d-42-71-d9/image/u_network_bptccd.mp4
CNN Architecture (U-Net)

Encoder (Contraction Path)

The first half encodes the input image into a feature representation at various levels.

Each block in our U-Net encoder subnetwork consists of two sets of convolutional (3x3 kernels with a single stride) and ReLU activation layers, followed by a 2x2 max-pooling layer.

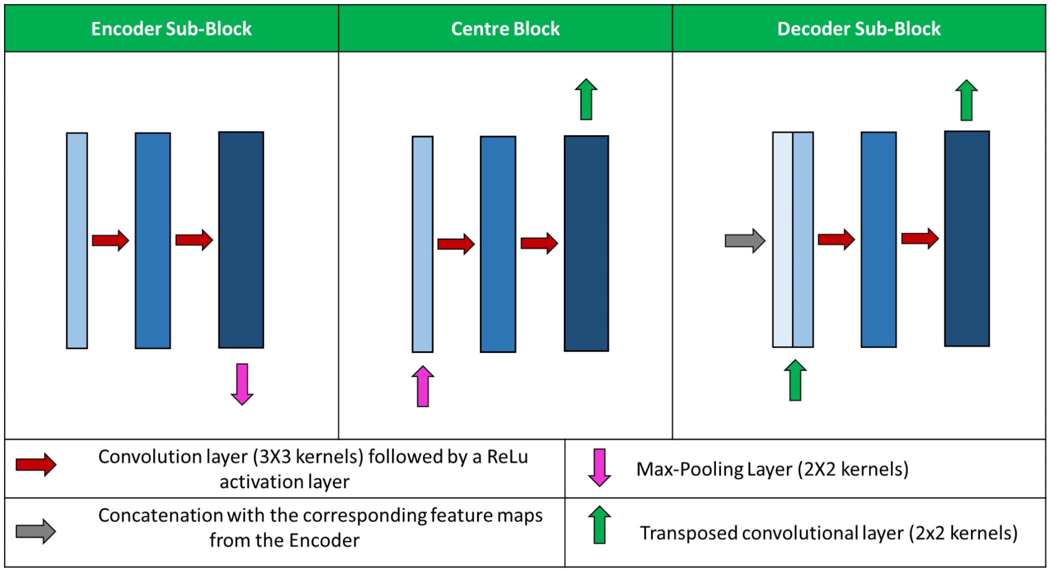
The bridge section (centre block) also consists of two sets of convolutional and ReLU activation layers for downsampling.

Decoder (Expansion Path)

Each block in the decoder subnetwork consists of a transposed convolution layer for upsampling.

We use skip connections by concatenating the output of the transposed convolutional layer with the feature maps from the encoder at the same level.

In each block, this is followed by two sets of convolutional layers with ReLU as an activation function.



Sub-blocks of U-Net architecture

The CNN model was trained on 4000 samples (20% of training samples used for validation) and tested on 1000 samples.

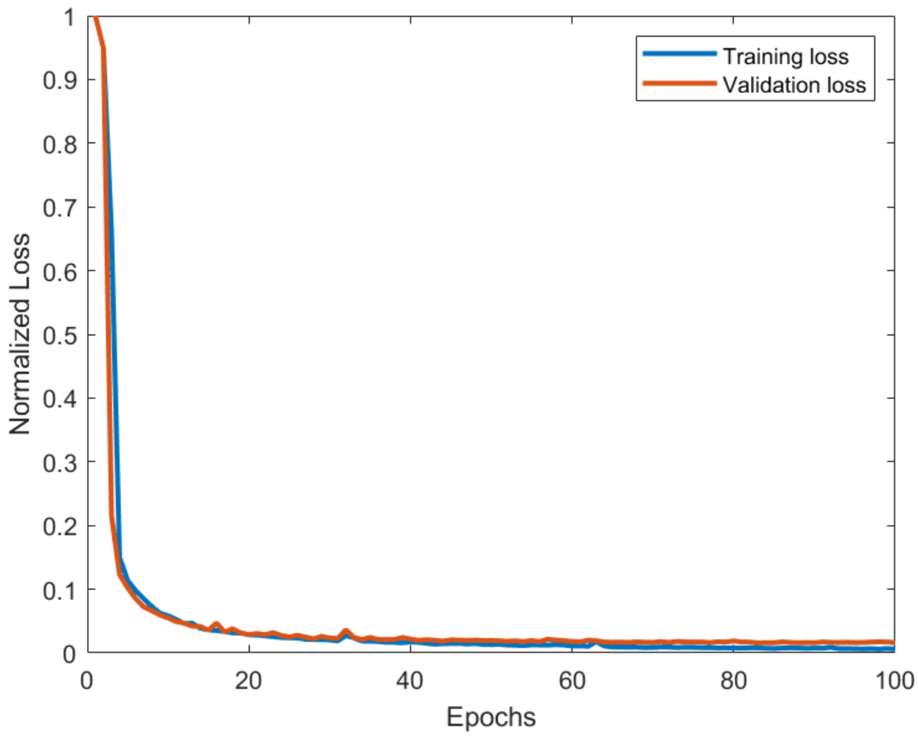
The weights of all the convolutional layers in the encoder and decoder were initialized using the 'He normal' intializer (He et al., 2015), while bias terms of all the layers were initialized to zero.

We used the Adam optimizer (Kingma and Ba, 2014) with $\beta 1$ equal to 0.9 and $\beta 2$ equal to 0.999 to update the weights, with a learning rate of 0.0001.

The U-Net model was trained for 100 epochs with a batch size of 128.

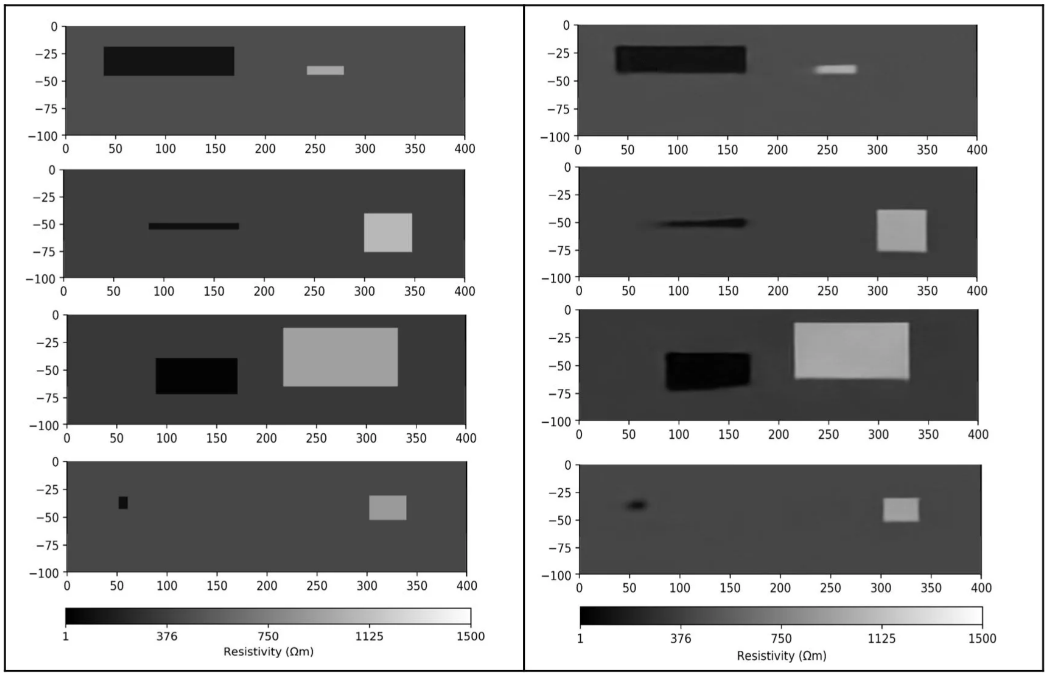
RESULTS AND CONCLUSIONS

Once trained, our U-Net model gave good predictions on the test dataset with a root mean square misfit of 2.86% on test data and 2% on training data.



Learning Curve (Misfit vs Epochs of U-Net

Our model was able to delineate both the blocks and the estimated resistivities of the blocks, and the background were close to the true values.



Inversion results: true models (left), predicted models (right)

The results confirm the efficacy and effectiveness of the proposed U-Net architecture in solving the 2-D ERT inverse problem for subsurface resistivity modelling.

FUTURE WORK

The next step is to invert the real (field) dataset using the proposed architecture and not only delineate blocks but also solve the layered earth inverse problem.

In this study, we only considered a resistive and a conductive block in a homogeneous background. We aim to use the proposed architecture to also delineate both resistive and conductive bodies in a heterogeneous background.

ABSTRACT

The interpretation of ERT data requires inversion which is challenging due to its nonlinear and ill-posed nature. We aim to solve the inverse problem using a machine learning technique that approximates the complex non-linearity using the data provided without specifying any geophysical or mathematical equations. Specifically, we make use of CNN with U-Net architecture to estimate the true subsurface resistivity model from observed apparent resistivity data (pseudosection). U-Net is selected because it works well when both input and output data are in the form of images and in the present work, input (pseudosection) and output (subsurface resistivity model) have spatial correspondence and existing local patterns.

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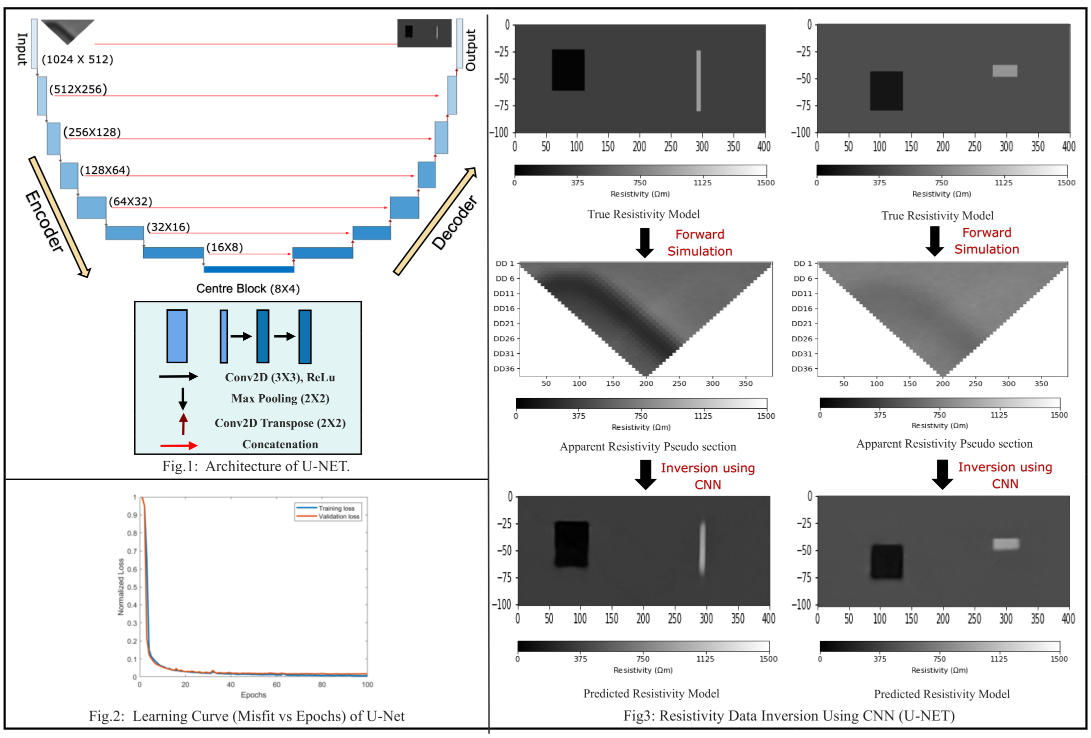

Fig.1: Architecture of U-NET.

Fig.2: Learning Curve (Misfit vs Epochs) of U-Net

Fig3: Resistivity Data Inversion Using CNN (U-NET)

(https://agu.confex.com/data/abstract/agu/fm22/2/3/Paper_1077432_abstract_1013603_0.png)

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