Geological Scenario Identification from Seismic Impedance Data

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Introduction:

The geological scenarios of different subsurface petroleum reservoirs are different. It is very important to identify the geological scenario of a petroleum reservoir for making good reservoir development decisions, like well placement decisions. Seismic data can help in doing so as it provides spatial information about the reservoir. This work attempts to identify the geological scenario from seismic acoustic impedance data using a convolutional neural network (CNN). A CNN is ideal for this problem because it can capture the spatial correlation in the data.

Problem Statement:

The goal of this project is to identify the geological scenario of petroleum reservoirs from seismic impedance data. In this project, two different geological scenarios are considered:

- Channel scenario
- Carbonate mound scenario

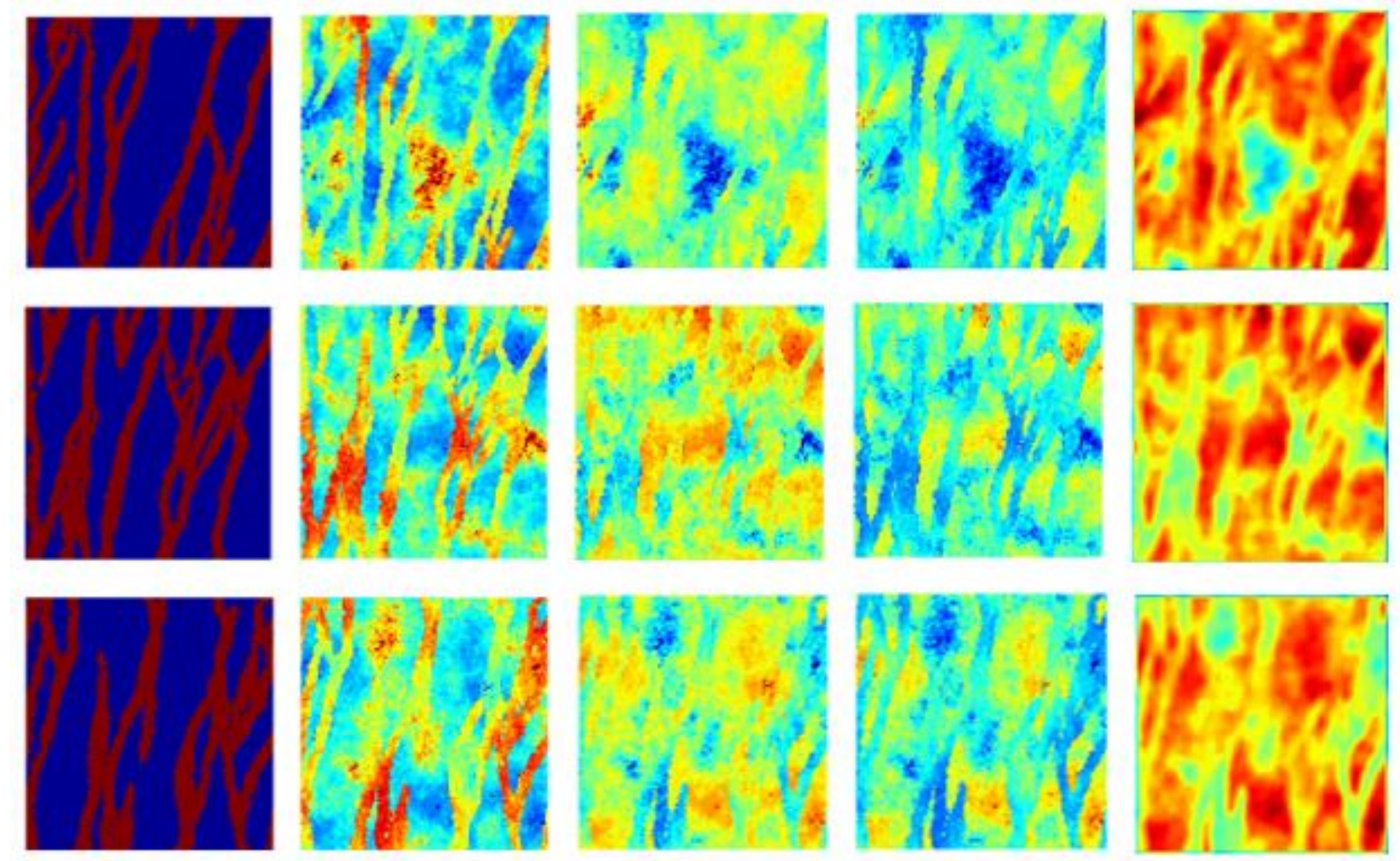
A synthetic dataset of seismic acoustic impedance for each of these two scenarios is generated, which is used to train and test a CNN. The performance of the trained CNN on test data is evaluated by building a confusion matrix.

Datasets:

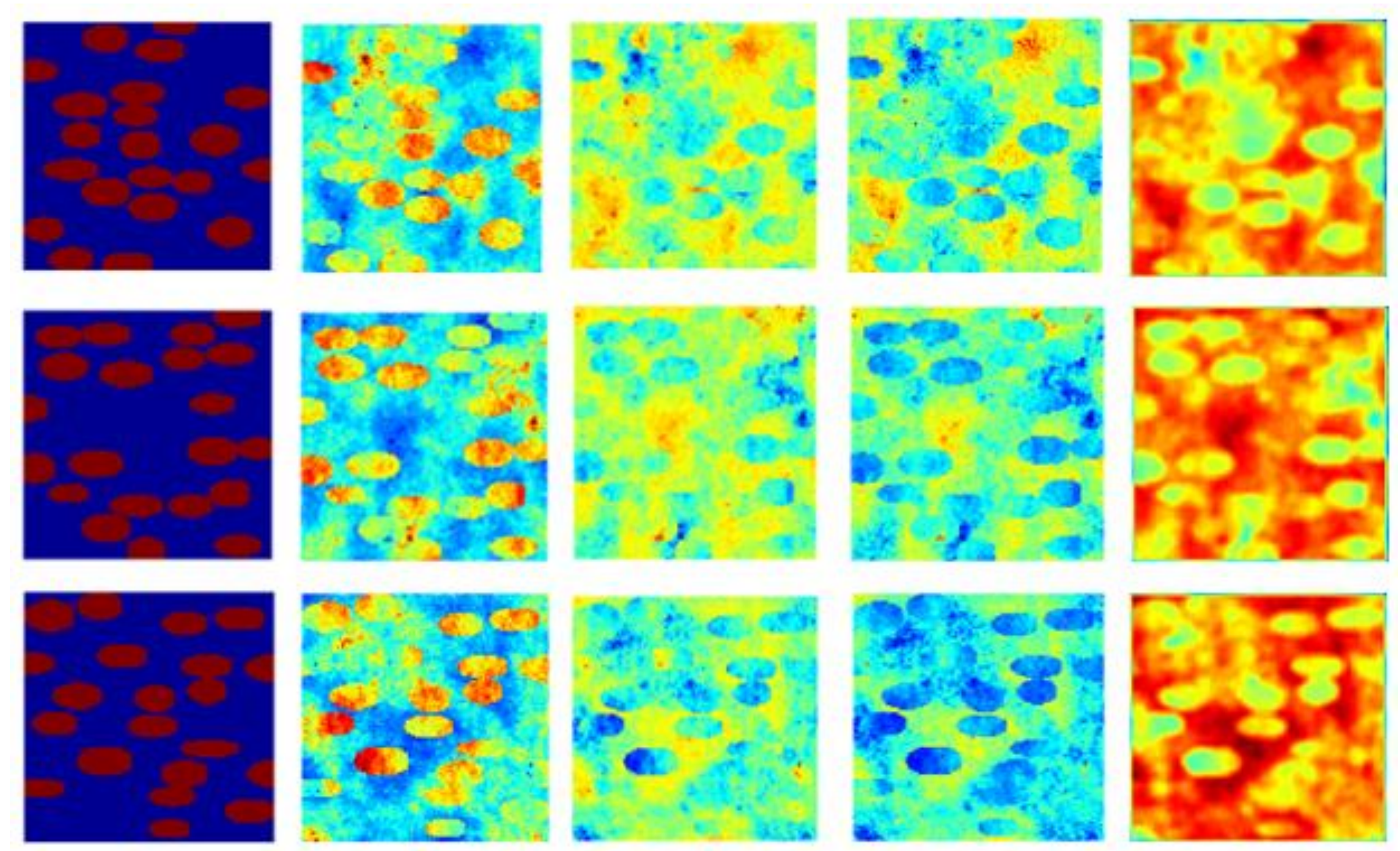
The synthetic dataset of seismic acoustic impedance is generated by the following steps:

- 1000 realizations of reservoir properties – facies, porosity and density – are generated for each geological scenario.
- The acoustic impedance (AI) is modeled using rock physics forward modeling (the constant cement model).
- A moving mean filter is applied to the AI to approximate seismic AI data which has low resolution.

Channel Scenario



Carbonate mound Scenario

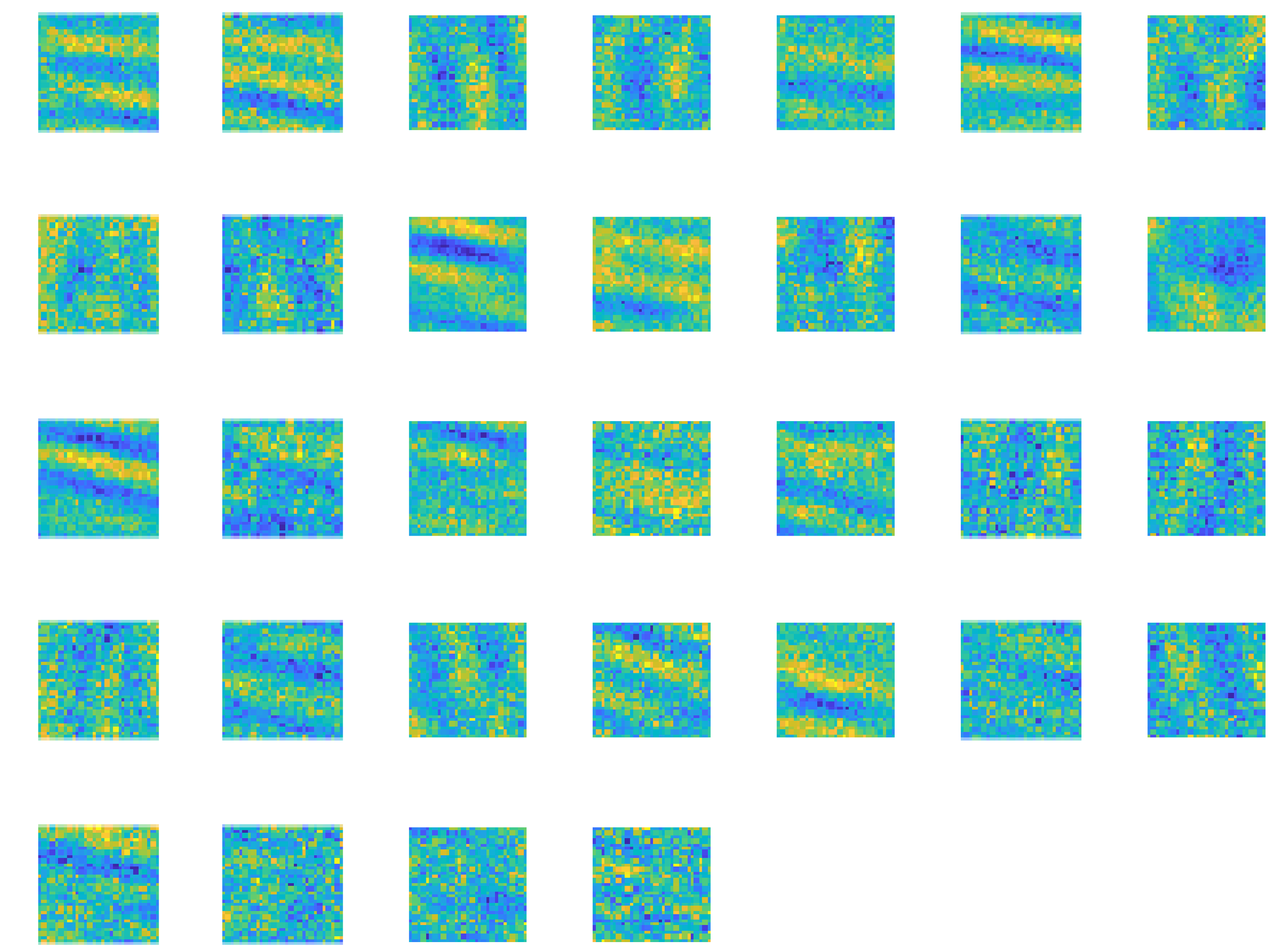


Methods:

A CNN is trained on the AI (seismic) dataset with layers:

- Convolutional (32 filters, 29x29, stride 1, padding 2)
- ReLU, Max Pooling (3x3, stride 2, padding 0)
- Convolutional (64 filters, 29x29, stride 1, padding 2)
- ReLU, Max Pooling (3x3, stride 2, padding 0)
- Fully Connected (64 layers), ReLU
- Fully Connected (2 layers)
- Softmax

First Layer Weights



Experimental Evaluation:

The trained CNN is evaluated on the test set. The results are summarized in the confusion matrix:

		Predicted	
		Channel	Mound
Actual	Channel	63	37
	Mound	0	100

Conclusions and Future Directions:

- The CNN detects mounds well, but not channels. The reason might be because many channel AI data have blobs in some areas which are interpreted as mounds by the network.
- Accuracy might be improved by transforming the data, e.g. by 2D Fourier transform.

References:

- W. J. Trainor-Guitton. On the value of information for spatial problems in the earth sciences. Stanford University, 2010.
- G. Yang, and J. Caers. Analysis of distance for discriminating geological and rock physics scenarios from 4D seismic data. SCRF annual affiliates meeting, 2015.