Intelligent digital rock physics assisting quantitative seismic interpretation

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Summary

Digital rock technology can quantitatively analyze the relationship between macroscopical elastic responses and permeability through pore structure feature in an image-and-compute way, which is helpful to realize quantitative seismic interpretation better. However, the limited number of samples and time-consuming analysis are limited to application of digital rock technology. Therefore, an intelligent digital rock physics analysis workflow including image processing, modelling, and parameters prediction can improve the construction efficiency of fine porosity-permeability relationship and rock physics template. Firstly, we proposed a multi-functional network to conduct all works of image processing, and then proposed a new generative adversarial network to generate richer samples with different pore structure and physical parameters based on different porosity distribution for expansion database, and finally proposed a multi-task network to synchronously predict multiple parameters to lower time cost on traditional numerical simulation, and formed a complete intelligent digital rock physics analysis workflow to assist quantitative seismic interpretation. Additionally, we provided evidences about the feasibility of this way.

Introduction

Rock physics have become a bridge linking geophysical responses and reservoir parameters, but it is difficult for traditional rock physics to build relationship between wave velocity and permeability. This is because we difficulty obtain pore structure information from geophysical data, and this information is highly relevant to the transport properties of rocks. Recently, benefited from the development of imaging technology, we can get digital form of rock and obtain pore structure from digital images and equivalent physical properties (Alkhimenkov et al., 2020; Hou et al., 2023). The way to study physical properties from images is called digital rock physics (DRP). However, traditional DRP analysis is limited to expensive sample acquisition and time-consuming simulation and image processing. Therefore, deep learning methods are introduced to solve these problems.

Although intelligent methods performed a good result on digital rock image preprocessing, modeling and parameters prediction, there are some limitation on these parts. Firstly, in the digital rock image preprocessing, most intelligent methods only focus on certain part of preprocessing such as image resolution enhancement, image segmentation, but there is not a method to conduct all these works. Secondly, in the sample modeling, the results may suffer from mode collapse problems for generating samples with complex pore structure. Finally, in the parameters, it is hard to perform multi-parameter high-precision simultaneous prediction due to interfere between different prediction tasks.

To solve these problems, we designed different deep learning methods and formed a feasible workflow. Firstly, we proposed a multi-functional network to conduct all works of image processing, and then proposed a new generative adversarial network to generate richer samples with different pore structure and physical parameters based on different porosity distribution for expansion database, and finally proposed a multi-task network to synchronously predict multiple parameters to lower time cost on traditional numerical simulation. Additionally, we provided some evidences about proposed workflow assisting quantitative seismic interpretation.

Method

In this paper, we proposed an intelligent method to realize intelligent digital rock physics analysis based on traditional workflow including image preprocessing, modeling and physical parameters prediction, and confirmed that we could extract pore structure information from digital rocks and join different parameters obtained by intelligent DRP analysis to build rock petrophysical interpretation chart, and hypothesized a possibility to use the workflow to assist quantitative seismic interpretation. The detailed steps are shown in figure 1.

![Figure 1: The potential workflow of intelligent DRP analysis assisting quantitative seismic interpretation.](image-url)
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For intelligent DRP analysis, firstly we proposed a generative adversarial network with segmented and perceptual information constraint (SPCGAN) to complete all works of image processing including image denoising, image resolution enhancement and image segmentation. In the network, based on our previous research, we used the generator network to conduct image denoising and image resolution enhancement and used the discriminator network to conduct image segmentation, and the details of proposed network can be seen in figure 2. The details of loss function can be found in our previous paper (Hou et al., 2021).

After that, we used preprocessed segmentation samples to train modeling network. To solve mode collapse problem of tradition intelligent methods, we proposed a new network called a style transfer network based on BicycleGAN structure (StyleBicycleGAN), and the structure of the network can be shown in figure 3. Our previous research found that images have multiple scale information, and we could extract these information from images and apply them into network through style transfer, and mode collapse can be effectively solved through the way (Cao et al., 2022). Therefore we used the generator network to replace the normal network of BicycleGAN, and redesigned network details in order to be suitable for 3D digital rock generation. Additionally, to improve the controllability, we used the porosity distribution of 3D digital rock at vertical direction as the latent factors.

Finally, to avoid the accuracy loss of multiple parameters prediction, we proposed a multi-task learning with multi-gate mixture-of-experts to synchronously predict elastic parameters from 3D digital rock samples (MMOEROCK3D), and the structure can be seen in figure 4. Based on our previous research (Hou and Cao, 2022), we extended the structure for 3D digital rocks, and used the network to predict P and S wave velocities and permeability. Additionally, the loss function kept original loss in our research.

Example
To test the method’s performance, we used practical data from Sichuan, China, and we divided them to some subsample with size of $256 \times 256 \times 256$. We randomly chose some subsamples as train set and others as test set.

We used common deep learning including DnCNN-10, DnCNN-30, SRCNN, SRGAN to compared with proposed method’s denoising and resolution enhancement functions, and used SegNet, UNet, SegNet based on residual block (ResSegNet) and UNet based on residual block (ResUNet)
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The results from figure 5 show that the results of proposed method is visually better than those of common image-enhanced methods, while the segmented results of SPCGAN difficultly find differences compared with other segmented methods visually.

Therefore, we supplemented porosity and permeability between proposed images and label images through lattice Boltzmann method (LBM), and the results show that the UNet method with the lowest relative error in porosity has the highest permeability error, while the SPCGAN method with the higher relative error in porosity had the lowest permeability error. So, we extracted pore-throat diameter distribution between the SPCGAN’s result and the UNet’s result to find the reason. We found that the small throat of the UNet result is more than those of the SPCGAN result and label sample, which means that UNet method exists problem of excessive segmentation. Overall, our method is beneficial for segmentation network, because we used as a SegNet of less layers as the discriminator of SPCGAN, but the accuracy is close to that of the SegNet with normal layers.

For samples modeling, we used the proposed method to generate new samples based on the porosity distribution of original models, and randomly choose three original models and generated models to show in figure 6. We extracted their pore structure feature including two-point probability function, two-point cluster function and lineal path function, and the result shows that there is a completely different distribution between original samples and generated samples. Additionally, we obtained porosity, bulk modulus, shear modulus and permeability of these samples through LBM and FEM. The results show that these samples have similar porosity but completely different physical properties, which proves that the method can effectively enrich the samples.

For multiple-parameters synchronous prediction, we used proposed modeling method to expand dataset and train the networks, and the results are shown in figure 7. We found that the accuracy of MMOEROCK is better than that of the single-task single-parameter network. This is because the R² scores of P wave velocity, S wave velocity and permeability of the former are 0.94, 0.97, and 0.84, respectively, and relative errors of those are 0.021, 0.018, and 0.031.
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respectively, while the $R^2$ scores of P wave velocity, S wave velocity and permeability of the later are 0.91, 0.93, and 0.70, respectively, and relative errors of those are 0.021, 0.021, and 0.051, respectively.

![Figure 7: Comparison of prediction results including (a) P wave velocity ($V_p$), (b) P wave velocity ($V_s$), and (c) permeability ($Perm$) in different methods with expanded dataset.](image)

Additionally, we provided some evidences about proposed workflow assisting quantitative seismic interpretation. We used above intelligent method to obtain P wave velocity ($V_p$), S wave velocity ($V_s$) and permeability ($Perm$) from digital rock images and extracted pore struct information including fractal dimension (FD) and Porosity to demonstrate that some relationships existing among these parameters could help us build rock physics template for obtaining reservoir parameters. We calculated 32 digital rock samples with different porosity and the crossplots between their different parameters are shown in figure 8. Firstly, Porosity shows a good power relationship with FD ($R^2$ score is 0.99) and Perm ($R^2$ score is 0.95), while it performs a perfect linear relationship with wave velocities (both $R^2$ scores are 0.99). Secondly, it can be seen that FD has a good Polynomial function relationship with wave velocities (both $R^2$ scores are 0.98), while the parameter has a power relationship with Perm ($R^2$ score is 0.94). Finally, Perm has a good polynomial function with wave velocities (both $R^2$ scores are 0.98).

![Figure 8: The crossplots between different parameters.](image)

Conclusions

We proposed an intelligent digital rock physics analysis flow to efficiently obtain rock’s permeability and wave velocities and provided an evidence that we can inverse permeability from seismic data directly or build a bridge between pore structure information and them (seismic data and permeability). The work is very meaningful and little works focus on application DRP technology in seismic interpretation. Our proposed workflow will provide a new and efficient way to obtain more information from seismic data.

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