Upscaling Experimental Measurements to the Field Scale Using a Machine-Learning-Based, Scale-Bridging Data Assimilation Approach

The researchers designed and conducted five research tasks. In Task 1, they developed supervised and unsupervised machine learning (ML) and deep learning (DL) tools that can automatically segment raw X-ray CT images. In Task 2, they developed physics-informed ML models to predict a rock’s transport property (e.g., permeability) using the 3D X-ray image of the rock. In Task 3, they developed a graphical user interface to manage and visualize rock CT images and lab-measured relative permeability (kr) curves from NETL’s Geoimaging Lab. In Task 4, they worked with the University of Illinois to collect well logging data. In Task 5, they developed a scale-bridging data assimilation framework to integrate rock’s transport properties obtained at various spatial scales and to calibrate the upscaled kr curves using well-scale observation data of CO₂ plume migration.

Data assimilation (DA) workflow for field-scale 𝐾, curve inference using field observation data of CO₂ saturations.
Benefits:
A well-trained supervised ML model can achieve segmentation quality as good as the training data at the millisecond scale. If training data are unavailable, unsupervised learning algorithms provide automatic, fast, and accurate segmentation. Processing time can be as short as seconds. ML and data analytics have been successful in solving many technical challenges in this UCFER project. Particularly, ML significantly accelerates digital rock image segmentation and flow property estimation. ML and data assimilation can be combined to match both the field scale observations (e.g., saturations) and intermediate, hidden variables (e.g., $k_r$).

Accomplishments:
Through this UCFER project, the researchers found that the IK-EBM method mitigates the partial volume blurring effect and leads to improved segmentation accuracy and high-quality training datasets. Convolutional Neural Networks (CNNs) achieve good performance of image segmentation because of local connectivity, weight sharing, and scalability robustness. Features extracted by the CNN not only include grayscale values but also contain geometric information and pattern. Supervised learning algorithms maximize the value of existing data, including raw images and segmentation images.

NETL Collaboration:
The team worked with NETL collaborator Dr. Dustin Crandall and his colleagues in the Geoimaging Lab. Using their X-ray CT image datasets of various reservoir rocks, they have developed a wide range of supervised and unsupervised ML models.

Relevant Publications:


Demonstrates that the low-resolution flow field information added into the input of the ML model greatly enhanced the model’s prediction accuracy. This proves that the physics-informed ML model has improved performance because of the combination of physics information and ML techniques.

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