Improving Resolution of a Fault Probability Map by a Deep Learning Generative Adversarial Network

Fan Jiang, Phil Norlund
Halliburton

9.29.2020 - 10.1.2020 – AAPG Annual Convention and Exhibition 2020, Online/Virtual

Abstract

Deep learning-based automatic fault interpretation workflows have grown more popular over the past few years, saving substantial interpretation time for geoscientists. However, fault prediction results from deep learning are characterized by the low resolution of fault probability that could extend real fault plane out of its true range. Additionally, the low fidelity of the fault prediction results create uncertainty locating the true fault. A traditional amplitude threshold scheme might reject useful fault information, resulting in an incomplete fault segment. In this abstract, a weighted generative adversarial network (wGAN) is implemented to improve the fidelity of the fault prediction results. GANs are deep neural net architectures composed of two networks, the generator (which generates new data instances) and the discriminator (which evaluates them for authenticity). This adversarial model can automatically discover and learn the regularities or patterns of input data to mimic data distribution. A weighting matrix is added to the generator to scale up the amplitude of the local patterns. The workflow used is designed in two steps. Step one involves model training, which uses synthetic fault data with exact position of the fault plane to train the adversarial model. The generator takes down-sampled synthetic fault data as input and creates new data that is fed into the discriminator alongside a stream of ground truth synthetic fault data. The discriminator attempts to authenticate the generated data compared to the ground truth synthetic fault data. Both networks attempt to optimize a different and opposing objective function in a zero-sum game. At the end, when the minimized loss function is achieved, the discriminator is unable to distinguish generated fault data from original fault data, and the adversarial model is saved for further process. Step two involves

prediction where down-sampled fault prediction data is used as input for the adversarial model, which generates new fault data and minimizes the cloudy effect with improved resolution. Once the adversarial model is trained by sufficient synthetic fault data, it can be applied to other fault data without retraining. Therefore, this method provides great flexibility and efficiency to improve the fidelity of the fault prediction results, it could also serve as a standard post-processing step to decrease the uncertainty after an automatic fault interpretation workflow.