Leveraging machine learning for fast and reliable 3D fault modelling

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ABSTRACT

Building the best possible 3D model from observed geological data is critical before grade estimation is performed. For many decades, 3D modelling of faults has been a challenging task. Currently, explicit or implicit modelling techniques are widely used to model faults. Explicit modelling is done manually by geologists based on their knowledge and expertise. The reliability of these models is dependent on the abilities of the geologists and creating them is a time-consuming process [1, 2]. On the other hand, implicit modelling takes a more mathematical approach to describe the fault geometry to combine the fault shape and fault frames [3, 4]. Godefroy et al. [5] introduced kinematics with implicit modelling methods and directly applied them to the implicit description of the faulted surfaces.

It is a challenging task to create 3D geological models comprising fault(s), as faults represent a discontinuity in geological feature(s) that are being modelled. Geological discontinuities and their uncertainties can be easily and consistently modelled using machine learning [6]. The underlying architecture of an implicit function has been developed and modified to provide the ability to create geological 3D fault models in three distinct steps; data preparation; building the fault geometries; and the use of machine learning to generate complex geological 3D fault models. This approach generates 3D models that fit the supplied data and geological knowledge of the generated fault(s), i.e., generates a geologically plausible 3D fault model. The new approach is fast and repeatable compared with existing techniques.

Case histories will be presented comparing conventional fault modelling practices with equivalent models generated using machine learning.

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