EGU22-11184
https://doi.org/10.5194/egusphere-egu22-11184
EGU General Assembly 2022

Robotic mining: a new approach to geological modelling

Hilco van Moerkerk and Paulina Dobrowolska
GEOREKA Software, Furth bei Gottweig, Austria (hilco@georeka.com)

Within the EU funded Horizon 2020 project ROBOMINERS (www.robominers.eu) we were challenged to consider how autonomous robotic mining could be integrated with geological modelling. How would an autonomous robotic miner know where and whether an orebody is worth extracting? The orebody and all related geological aspects would need to be modelled in a comprehensible, self-containing format the robot can use directly. To this end we envisioned a robot that would know where the orebody is, its important characteristics, and would have the ability to interpret the orebody in real-time and update its geological knowledge of the orebody as it excavates.

The modelled orebody could only be approximate at the robot scale (estimated at 1m maximum diameter!) as detailed information would be lacking. This led to re-evaluating existing geological modelling practices to see how they would fit within the robotic mining concept.

In our work we developed a novel approach to traditional geological modelling by combining three essential elements:

- Replacement of blocks in block modelling with tetrahedra
- Functional modelling framework to create model descriptors
- Machine Learning

A tetrahedron is the most basic 3D element, similar to a triangle being the most basic 2D element to represent objects. Tetrahedra can be made to accurately reflect a boundary and are therefore always either inside or outside of that boundary. They are commonly used in Finite Element Methods (FEM) and have found their way into geophysics, geomechanics and flow modelling, but until now, not into geological modelling. Another major advantage is that a tetrahedral grid can be constructed at multi-resolution scales. However, it also means geological features need to be described in a way that allows them to be represented at those scales (e.g. mine scale versus robot scale).

One method to deal with these scale issues is to use a functional representation: representing geological features with (mathematical) functions. With functions, a value from that function at ANY point in 3D space can be retrieved to see if that point is either inside or outside of a unit. Functions have been used under the Implicit Modelling (IM) banner. However, the functions can be also seen as classifiers between regions. Machine Learning's (ML) core functionality is to provide is a mechanism for classifying data and estimate values or labels to unknown points. In our work, were therefore integrated high performance ML algorithms into IM.

With these three key elements we developed a system that can represent a complete 3D geological model in a consistent and ordered way by describing it rather than actually creating it. The model description can then create an optimized FEM model at any resolution when needed, even though the descriptor does not change. The ultimate aim is that the descriptors and functions will be used directly by the robot to optimize its path planning, without needing large data transfers.