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Rapid updating of resource knowledge with sensor information

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Introduction

Resource models are generally constructed from directly observed data (e.g., grades of drill cores) that have relatively high accuracy. However, the accuracy of resource models is therefore limited by the scale on which the data are collected. As mining progresses, more information becomes available on different scales from various types and sources of data (e.g., blast hole samples, sensors on drill rigs, conveyor belts and draw points). This continuous stream of production data can be used to update resource knowledge in near real-time.

The ensemble Kalman filter (EnKF) has been successfully applied to update resource and grade control models [1, 2]. However, due to the Gaussianity assumption, EnKF must be combined with some kind of Gaussian transformation, such as a normal score transform. Multi-Gaussian transformations can yield better results in terms of reproducing relationships between multiple grade variables. This poster presents a case study demonstrating the application of the ensemble Kalman filter and the projection pursuit multivariate transform (PPMT) for sequential updating of multivariate geostatistical models.

Ensemble Kalman filter

The updating step of the EnKF can be expressed as:

$$Z_{t+1} = Z_t + K(Y_t - AZ_t), \tag{1}$$

where Z_t and Z_{t+1} are prior and posterior ensembles, respectively, K is a Kalman gain matrix, Y_t are observations and AZ_t are model-based predictions.

The optimal Kalman gain matrix is given by:

$$K = C_{t,t}A^T(AC_{t,t}A^T + P), \tag{2}$$

where $C_{t,t}$ is the covariance matrix for state t, A is a production matrix, and P is the precision of the observations.

Projection pursuit multivariate transform

The PPMT methodology is based on iteratively searching for projections with maximum departure from Gaussianity followed by a normal score transformation along those projections [3]:

$$Y_{(i+1)} = R_{(i)}^{PP^{-1}} \Psi_{(i)}(Y_{(i)} R_{(i)}^{PP}), \tag{3}$$

where $R_{(i)}^{PP^{-1}}$ is an orthogonal rotation matrix and $\Psi_{(i)}$ is a normal score transformation applied to the first dimension of the rotation matrix.

Synthetic dataset

To demonstrate the performance of the proposed algorithm, a synthetic dataset from [4] was used to produce 200 initial geostatistical realisations (Fig 1). To do so, PPMT was applied to the original 2,000 drill hole samples, and the resulting factors were individually simulated. Back transformation of geostatistical realisations shows that the initial simulations reproduced the complex multivariate relationships (Fig 2).

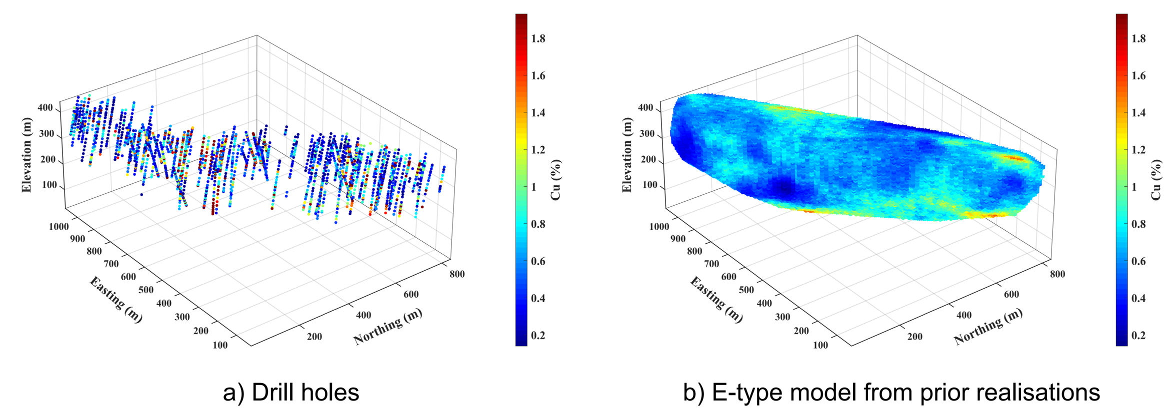

Fig 1. 3D view of (a) drill hole data and (b) e-type model from 200 geostatistical realisations.

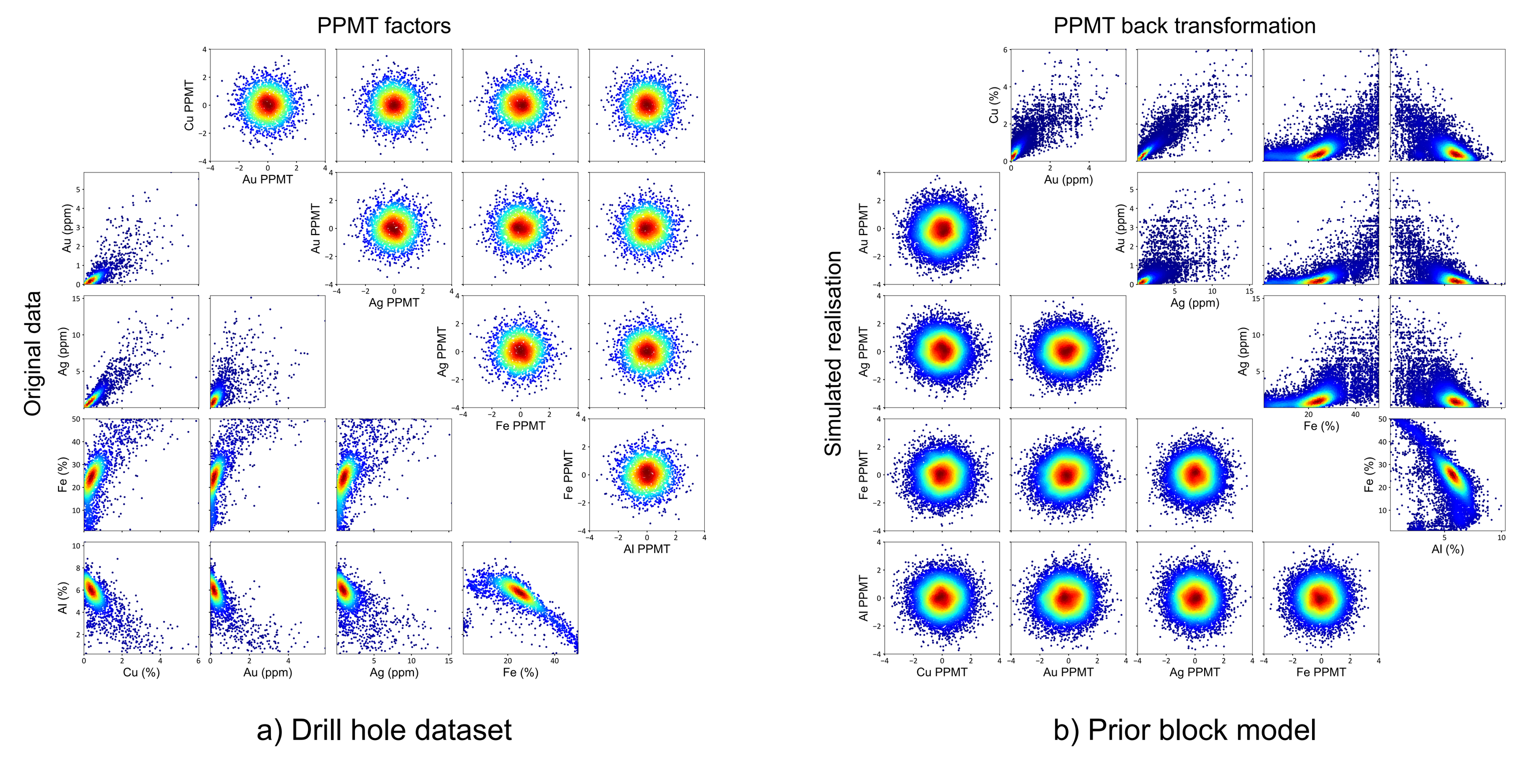

Fig 2. Cross plots of (a) drill hole dataset and corresponding PPMT factors; (b) simulated realisation and PPMT back transformation results.

Data assimilation

Fig 3a shows the 10,000 synthetic observations produced with identical statistical properties to the original drill hole data. These observations were forward transformed to the multi-Gaussian space using PPMT before applying the EnKF to update prior realisations. As seen in Fig 3b, the e-type model from 200 updated realisations significantly differs from the initial e-type model in Fig 1b.

The proposed approach helped to reduce the MSE and improve the R^2 of model-based predictions by 70-75% and 75-96%, respectively (Fig 4). Moreover, the reproduction of multivariate relationships was not affected by EnKF because of the multi-Gaussian transformation (Fig 5).

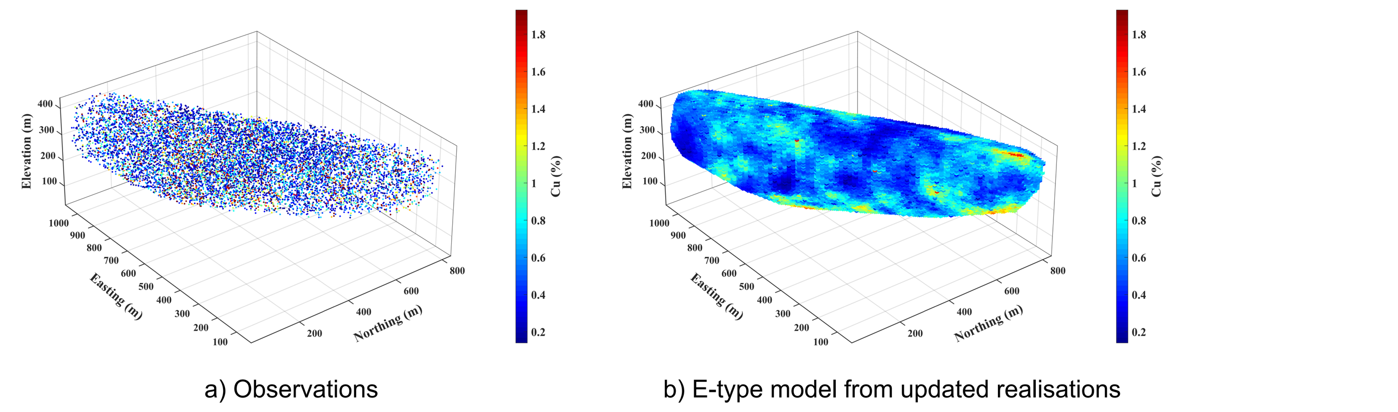

Fig 3. 3D view of (a) new observations and (b) e-type model from 200 updated realisations.

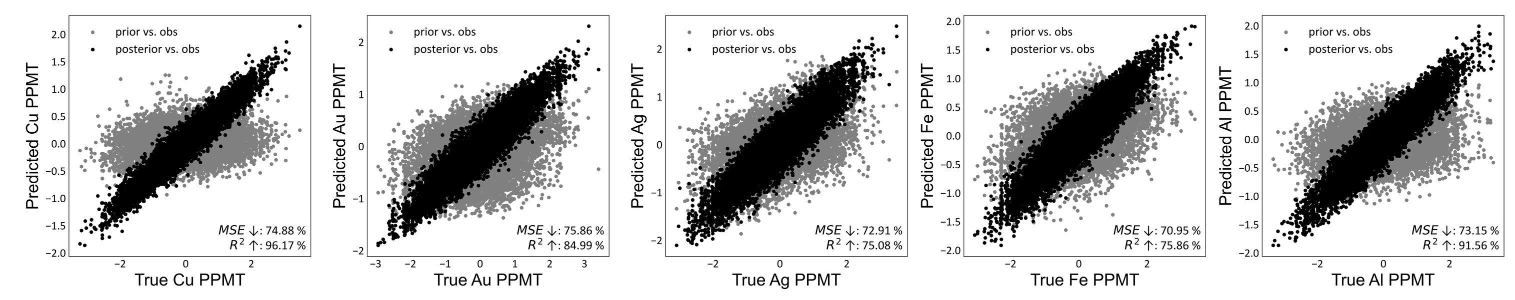

Fig 4. Model-based predictions vs. actual observations before and after rapid updating.

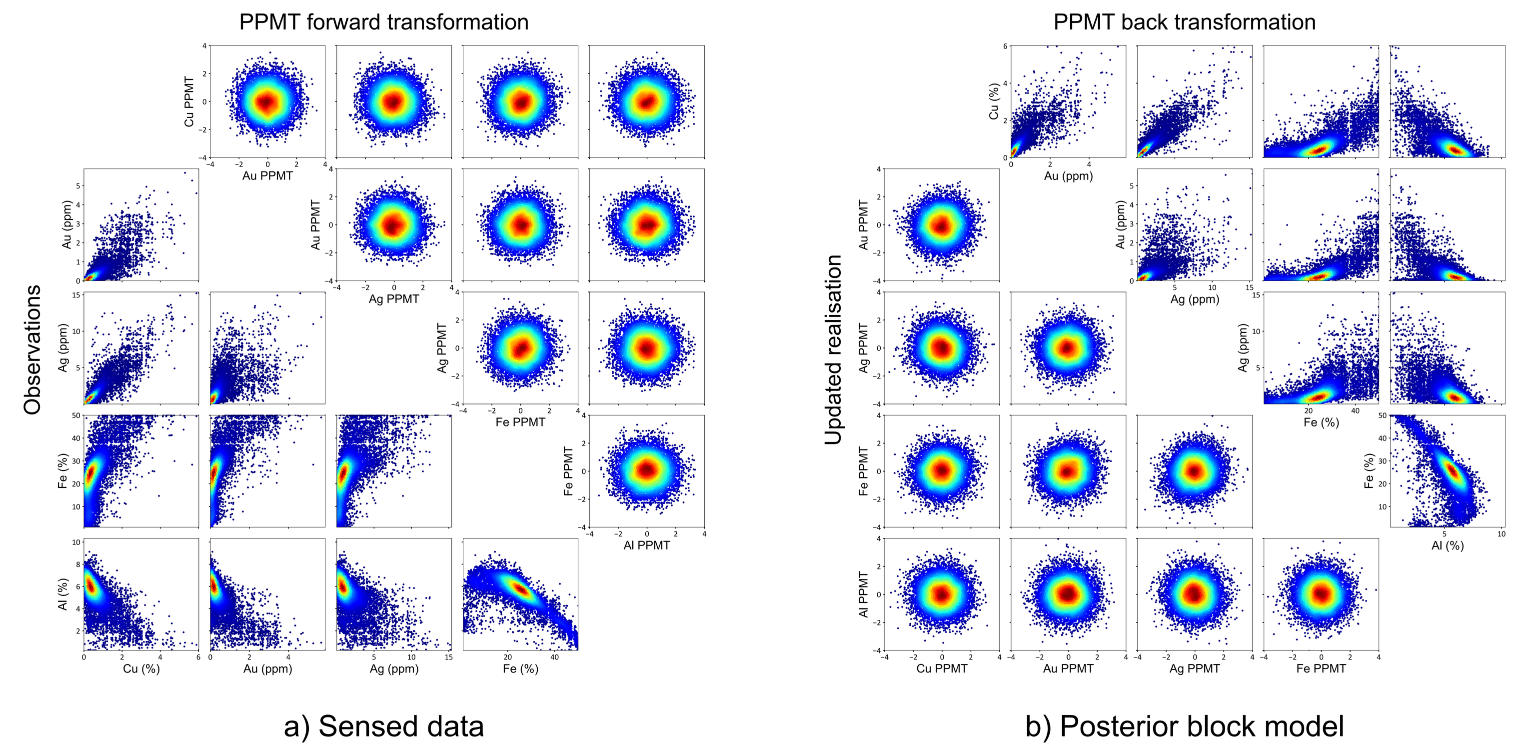

Fig 5. Cross plots of (a) observations and PPMT forward transformation results; (b) updated realisation and PPMT back transformation results.

Conclusions

EnKF, combined with PPMT, can update multiple cross-correlated variables in near real-time without affecting their relationships. The process of rapid updating can also be automated, providing mining engineers and geologists with accurate and up-to-date resource knowledge whenever needed. In future work, we will extend the rapid updating process to other variables, such as geological domains and geometallurgical properties.

References

[1] Benndorf J, Buxton MWN (2016) Sensor-based real-time resource model reconciliation for improved mine production control – a conceptual framework. Min Technol 125(1):54-64.
[2] Wambeke T, Benndorf J (2017) A simulation-based geostatistical approach to real-time reconciliation of the grade control model. Math Geosci 49:1-37.
[3] Barnett RM, Manchuk JG, Deutsch CV (2014) Projection Pursuit Multivariate Transform. Math Geosci 46:337-359.
[4] Hoffmann J et al (2022) Modeling Geospatial Uncertainty of Geometallurgical Variables with Bayesian Models and Hilbert–Kriging. Math Geosci 54:1227–1253.