Cooperative Inversion: A Review

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SUMMARY

Cooperative inversion has the potential to significantly improve subsurface imaging. However, success or failure can be highly dependent on knowledge of underlying site specific geological and petrophysical relationships. Combinations of structural or textural seismic attributes can be integrated into geostatistical clustering to provide a framework able to carry inversion of lower resolution EM or potential field data to an outcome with improved detail and accuracy. Cross-gradient type methods link direction of change of different physical parameters within inversion. Outcomes will be dependent on the presumption that the direction of change of petrophysical parameters like velocity, density and electrical conductivity are indeed linked. Cooperative and joint inversion need to be validated by information harvested at drill sites. Here new low cost multi-scale, multi-parameter logging while drilling technologies could be designed to feed real time imaging based on cooperative inversion. We will; (i) examine theoretical possibilities, (ii) give examples of practical successes and failures, and (iii) consider the future of cooperative inversion.

INTRODUCTION

Various forms of Joint and Cooperative inversion present the possibility of significantly improving subsurface imaging (e.g. Gallardo and Meju 2004, Moorkamp et al. 2013, Linde et al. 2006, Doetsch et al. 2010, Zhou et. al. 2014, Le. et. al. 2017, Lines et. al. 1988, Takam Takougang 2015). By "significantly improving", we mean the outcome should be a higher resolution, more accurate representation of true subsurface parameter distributions. For electrical methods like magnetotellurics, the parameter is electrical conductivity and for seismic reflection methods the parameter could be acoustic impedance. However there are other less obvious parameters that may contribute to, or be improved by, cooperative inversion. Examples are, seismic texture (distribution of seismic reflectivity) or direction of change of petrophysical parameters. Other subtleties like frequency dependence (Revil 2014) or anisotropy may be out of reach for standard inversion but come into focus if cooperative inversion affords a higher levels of certainty over key geometries in the subsurface. The questions is; how can the potential of cooperative inversion be realized and equally how can we avoid the many traps that lurk in the shadows of what joint or cooperative inversion promise?

Cooperative Inversion

How should cooperative inversion be defined relative to joint inversion? This comes down to the way constraints are introduced to the inverse problem. For joint inversion, constraints are usually introduced explicitly via the objective function. For cooperative inversion, constraints are typically introduced implicitly via the initial model or by manipulating spatial distribution of inversion parameters such as "smoothness" or discretization. High resolution seismic reflection imaging is ideally suited to constrain large scale geometries for inversion of lower resolution potential field or electromagnetic data. If high contrast boundaries are precisely known from reflectivity imaging, then relaxation of smoothness requirements (e.g. covariance coefficients) across these boundaries may significantly improve inversion outcomes. Relaxation of smoothness constrains permits rapid change of parameters like conductivity across high contrast boundaries. Comprehensive reviews of these and many other concepts in cooperative inversion are provided in Le, et. al. 2017 and Moorkamp, 2017. Given a sufficiently flexible inversion scheme cooperative inversion may require minimal or no modification to baseline code.

We show how multivariate statistical methods like self-organizing maps (SOM), principle component analysis, fuzzy cluster techniques, and K-mean analyses can be integrated into cooperative or joint inversion (Bedrosian et al. 2007; De Benedetto et al. 2012; Di Giuseppe et al. 2014; Dubrule 2003; Kieu and Kepic 2015; Klose 2006; Roden et al. 2015; Ward et al. 2014, Sun and Yaoguo, 2016). We also consider the potential of modern machine learning or "Deep learning" (LeCun, 2015) in cooperative inversion.

The nature of the target is also a material consideration. Classic problems suited to cooperative or joint inversion are; imaging of salt domes in the search for hydrocarbons or exploration for mineral ores in crystalline basement below thick barren cover. In our presentation we will explore the successes, failures and future directions for cooperative inversion.

CONCLUSIONS

Cooperative and Joint inversion combined with modern machine or "Deep learning" (LeCun, 2015) is likely to play a significant role in the future of exploration geophysics. Weaknesses can be incurred by "hard coding" complex or unrealistic relationships between petrophysical parameters into the objective function of the inverse problem. For the moment a traceable process that improves the start model and distribution of "smoothness constraints" appears to work well. Certainly modern massively parallel computing make this approach viable. Current inversion software probably needs a major overhaul. Future software should aim to accept multiple data streams direct from geophysical instruments and drilling to achieve real time subsurface imaging based on multiple inputs.

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