Orientation Estimation with an Adaptive Moving Window

Maksuda Lillah and Jeff Boisvert

Local windows are often used to determine local orientation for input to geostatistical algorithms that can consider locally varying anisotropy. Often the user fixes the window size, but this causes issues when the scale of the geological body changes within the domain of interest. Smaller windows tend to find isotropic features in larger bodies as the window is too small to capture the appropriate orientation. Large window sizes do not capture smaller scale variations within the window. Moreover, if the orientation of the body is rotated 45 degrees from the input window orientation, the majority of the feature would not be contained in the window and may not be captured. A methodology to adapt the window size to local features is presented. Input data can be continuous or categorical but must be exhaustive.

Introduction

There are many techniques for determining the orientation of exhaustive data, see paper 107 in this report. These techniques can be improved upon by selecting a local window for orientation calculation that is tuned to local features. In areas where features are large, the window size for orientation calculation should be large; in areas where features are smaller, the window size for orientation calculation should be small. Window size and orientation should be tuned to the scale of local geological features. An optimal search area that best defines local features is desired. In this paper we deconstruct the idea of a local 'window' in that our search area is defined by an ellipsoid (an ellipse in 2D) with a particular orientation. In 2D an ellipse is parameterized by:

$$\left(\frac{x-x_c}{a}\right)^2+\left(\frac{y-y_c}{b}\right)^2<1\ ; \qquad \textit{(defines the portion inside an ellipse)}$$

where, a,b are the length of major and minor axes, (x_c,y_c) is the pixel of interest.

The same inequality can be written in a matrix form; multiplying by a simple rotation matrix will then rotate the ellipse in the given direction. A local window is defined by three parameters, ***a, b*** and the rotation angle ***(α)***. We can restate the main objective here: for a given location we want to determine the optimal combination of a,b,α that results in the maximum reliability (r) of the tensor. Reliability is calculated from the analysis of the local tensor (see CCG paper 107 in this report).

r=(difference of eigenvalues)/(sum of eigenvalues);

Full optimization of the local window would be accomplished by testing all combinations (a,b,α) and selecting the combination that results in the minimum r value. The user selects the potential values for (a,b,α) and they are exhaustively searched; this will be referred to as full optimization. The resulting LVA field follows the underlying features quite closely (Figure 2). However, full optimization is only computationally feasible for small models. Additionally, in 3D there would be six parameters to optimize. Instead a partial optimization scheme is implemented where all combinations of (a,b,α) are not searched. In general, local search windows should be similar to the optimized search windows nearby. As a result, the full optimization at the first point (top left corner in Figure 2) is performed and then for all subsequent grid points at least one neighboring point will be found with a previously optimized window. This is taken as the initial parameters to use at the new location and a line search in each variable (a,b,α) results in the new optimum. This saves significant computational effort and performs better in 3D. To ensure that partial optimization is efficient measure of the full adaptive process we can compare the resulting LVA map (Figures 2 and 3).

The partial adaptive window process can be improved upon by re-estimating each point once a base LVA field in generated. Here we use the previously optimized parameters as initial guess in the new estimation and randomly visit locations and perform another line search. Re-visiting and therefore recalculating LVA results in a higher mean reliability (Figure 4). Partial optimization can be easily extended to 3D and the results for a 3D example are shown in Figures 5-7. The input model is 115x128x11. Similar results as found in 2D were found in 3D.

Concluding Remarks

Customizing the local region for determination of local orientation results in maps of orientation that are more consistent, adapt to changing scales of continuity, and maximize reliability. Reliability has been found to be an effective measure of the goodness of the local direction of anisotropy.

References

Boisvert, J B. Geostatistics with Locally Varying Anisotropy, PhD (2010). University of Alberta, Canada
Issaks, E, Srivastava, R M. Introduction to Applied Geostatistics (1989). New York, Oxford University Press
Deutsch, C V. (2002) Geostatistical Reservoir Modeling. New York, Oxford University Press

Figures

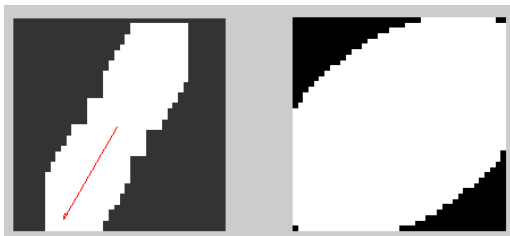

Figure 1: Ellipsoid window example. Left: model with two categories (white=1, black=0), local orientation shown as a red arrow. Right: Local optimal search window. White=areas that are considered for tensor analysis, black=areas excluded from analysis.

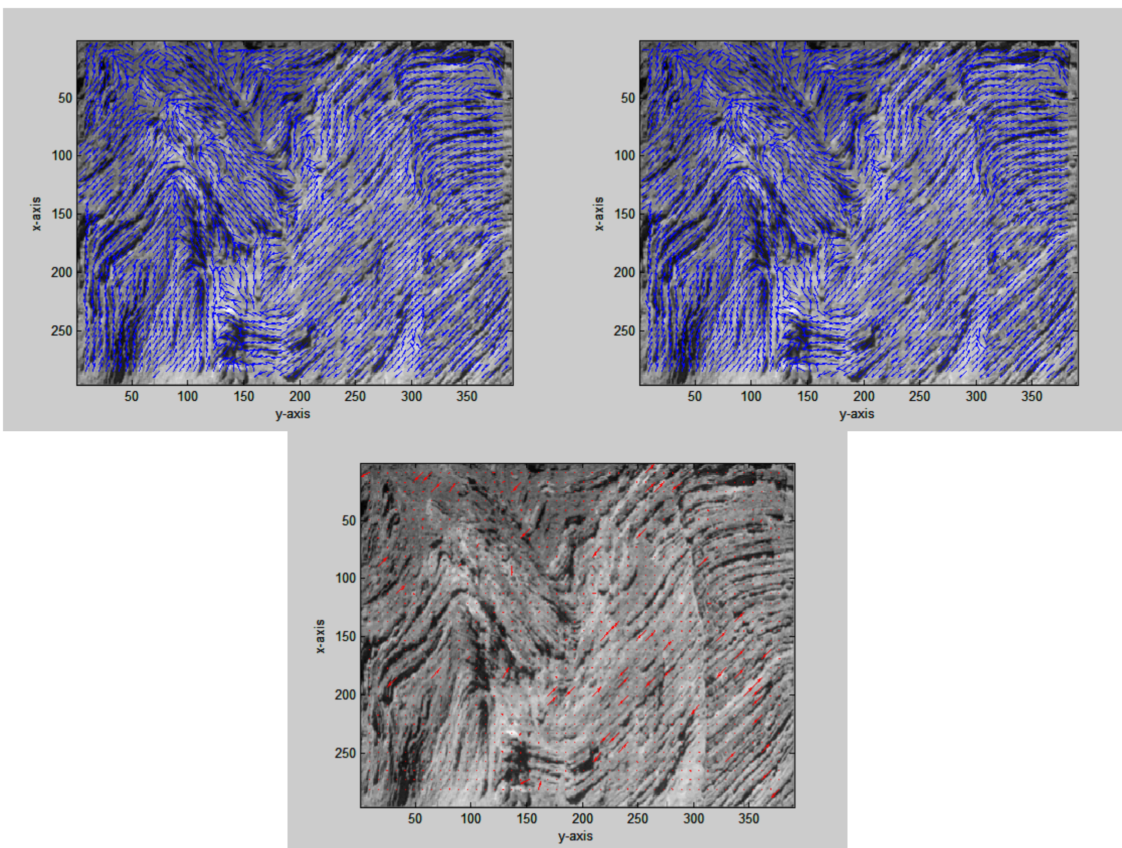

Figure 2 Left-The full optimization. Right: Partial optimization *a* (10-16), *b/a* (0.6-1) angle (0°-180°). Below-Difference in angle between The full and partial optimization.

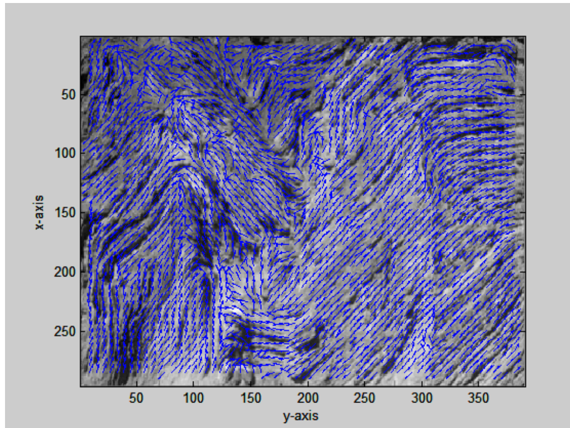

Figure 3: LVA field after randomly visiting 10000 points and re-optimizing the orientation.

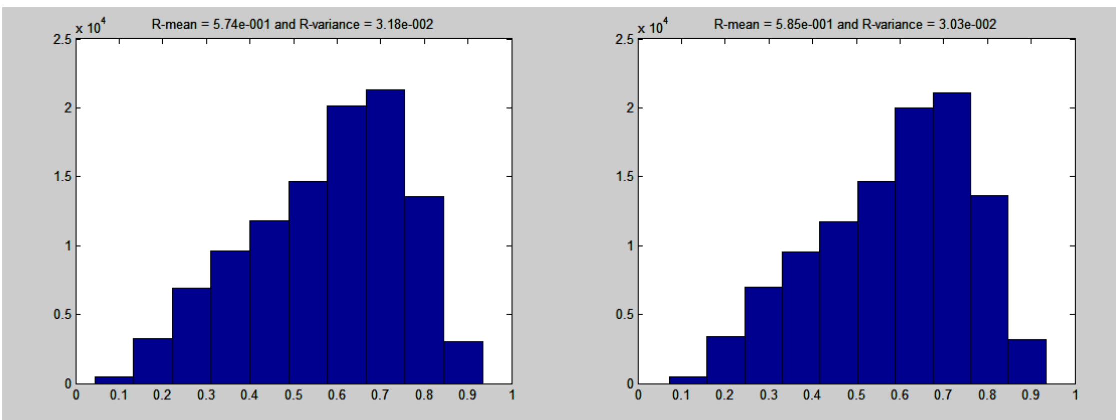

Figure 4: R-histogram (partial_opt – left, randomly visiting each location once – right).

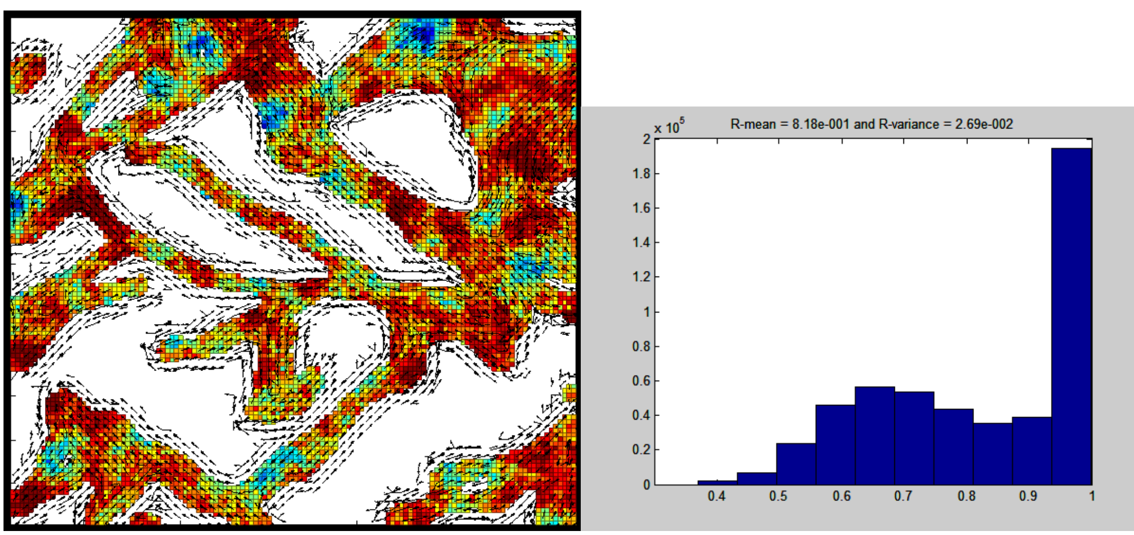

Figure 5: Left-Resulting LVA using partial optimization. Right-Histogram of reliability.

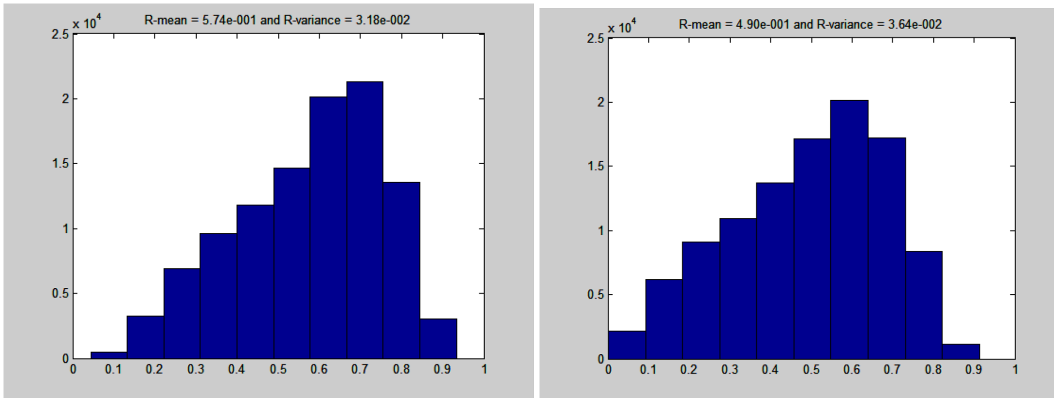

Figure 6 R-histogram (partial_opt – left, no opt - right)

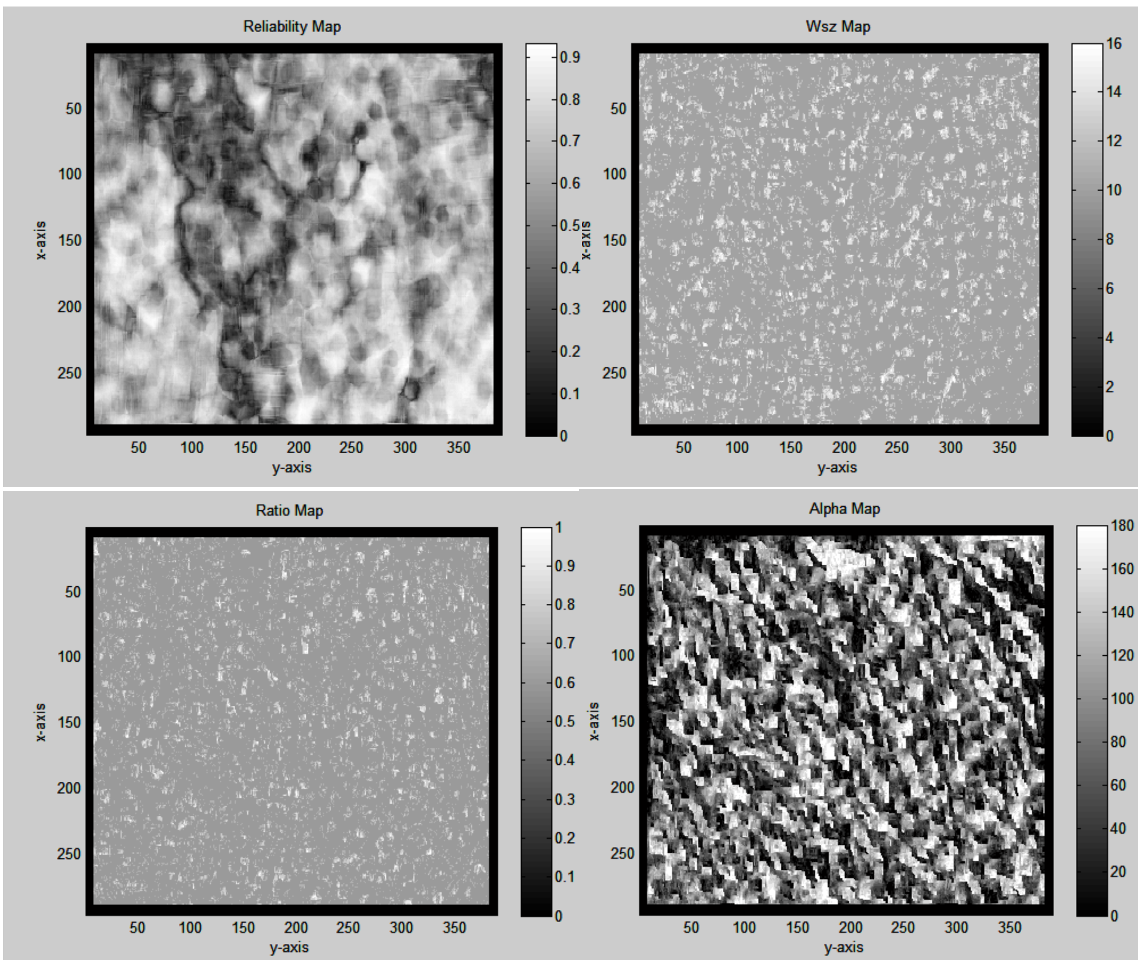

Figure 7: Maps of reliability and parameters for the partial optimization