Solid Earth Discuss.,
https://doi.org/10.5194/se-2019-104-AC2, 2019

Solid Earth Discussions

Interactive comment on "An automated fracture trace detection technique using the complex shearlet transform" *by* Rahul Prabhakaran et al.

Rahul Prabhakaran et al.

r.prabhakaran@tudelft.nl

Received and published: 13 October 2019

The authors would like to thank Dr. Lamarche for the reviewer comments. Please note our responses to the specific comments below.

Reviewer Comment #1 Introduction.The amount of literature on the topic is growing too fast at the moment. You cannot cite all of them, so please add "e.g." in your text.

Author's Response to Reviewer Comment #1 We have modified the particular citations within the Introduction section of the marked down manuscript.

Reviewer Comment #2 4.1.2 Automated detection artificially fragments the large fractures, what are the methods, limitations, threshold values to prolongate traces and form large fractures?

Author's Response to Reviewer Comment #2 This is a very valid comment. Automated techniques can result in fragmentation with and without gaps. If the fragmentation happens without a gap, then the sum of lengths of individual segments that constitute a single trace is equal to full trace length. Our implementation fits polylines to intersecting pixel clusters (representing intersecting fractures), inserts a branch point, and stores the polylines separately. We do not see this kind of fragmentation as an issue when such a fragmented DFN is used for geometric input for flow / geomechanics simulation. This is because the process of meshing models with explicitly specified DFN geometry would in any case require the specification of all intersection points (or the forced fragmentation of long fractures). If an interpreter wants to identify certain segments as belonging to one fracture set, regardless of the number of intersections, then more information is needed to arrive at such a decision. This information could be based on orientation, abutting relationships, mineralogical study of cement infill, and fluid inclusion studies. Fracture strike is easily calculated (since each polyline is georeferenced). To link fragmented traces based on strike, we could implement simple heuristics. In case of fragments that share an intersection point (or branch point), we could parse through the stored list of fractures, identify those with similar strike and enforce them as one fracture set. However, strike alone may not be enough to identify whether fragments are to be joined as a single set.

A single fracture (as interpreted by the geologist) could also be fragmented without being cut by other intersecting fractures. This could happen in the case of false negatives (shadows or shrubbery within an open fracture) that cause fragmentation of fractures with gaps in between them. This kind of fragmentation affects the topology of the network. The role of fracture network topology on fluid flow response has been the focus of many works such (for example Hardebol et al, 2015). The simplest strategy in this case would be to use a linking threshold plus similar strike to bridge these gaps and store the fragments as a single fracture. Such approaches are already available (such as NetworkGT by Nyberg et al, 2018). The uncertainty in topologies (in terms of the relative I-Y-X nodes within the network) maybe studied to further quantify simulation responses. However, these methods may not generalize well in all cases, especially when the fragmentation is due to noisy data.

Within the machine learning literature, there has been some progress on deep graph algorithms that can perform graph extrapolation (Cordonnier and Loukas, 2019). These techniques have been developed based on the premise that naturally occurring graph structures are almost always, incompletely sampled. Therefore, natural networks would require manual intervention to add edges or nodes based on the relevant domain expertise. The edges may need to be extrapolated from a set of training graphs (that encapsulate features of a complete natural network) which can then extrapolate edges to an incompletely sampled graph using generative graph neural networks. The application of such techniques is beyond the scope of this manuscript but we will attempt this in future work. Collected field observations such as Lamarche et al, 2018 that specify dimensional thresholds for fracture linkage could be useful for such an attempt.

Reviewer Comment #3 4.1.3 Would be nice to have a better constrained comparison of automated versus visual extraction of fractures from French example. In addition to the P21, could you provide data like strike (rose diagram or histograms), length (histogram), number of fractures. . . that will help understanding the nature of the difference between both visual and automated surveys. Would be nice to have them for all of the 3 field examples.

Author's Response to Reviewer Comment #3 We have added rose diagrams, cumulative length distributions, and number of traces to both manual and automatic interpretations corresponding to the Parmelan (Fig.1(f) and Fig.1(g)) and Brejoes examples (see Fig.2 for the comparison and Fig.3 for the rose plots and cumulative distributions). Please note that for the Bingie Bingie examples, Thiele et al, 2017 have not released vectorised assisted interpretation trace maps and hence we created vectorised trace maps from the raster images presented in Thiele et al, 2017 (see Fig.4(k) and Fig.5(k)). This additional plot is used only for visual comparison with Fig.4(h) and Fig.5(h). To quantitatively compare between automatic and assisted interpretations, rose plots are added in Fig.4(f), Fig.4(i), Fig.5(f), and Fig.5(i). The cumulative length distributions are added in Fig.4(g), Fig.4(j), Fig.5(g), and Fig.5(j).

Reviewer Comment #4 Having a priori ideas on fractures while visually interpreting images is not a bad thing. Indeed, the geologist is aware of the brittle processes and their limitations on the fracture geometries. This, to my opinion, is precious for visual "human-hand" fracture tracing.

4.3: No difference is made between geological features such as fractures, bedding, other, when automated tracking is performed. So, the need to impose a priori structures or preferred fracture trends is important upstream and worth in order to avoid interpreting excessive or ghost fractures.

Author's Response to Reviewer Comment #4 We agree that a priori ideas are, in general, useful in performing manual tracing. In Page 8, Lines 29-31, we mentioned this to highlight the fact that an interpreter who hand traces at a fixed zoom level, would perhaps not identify disconnected fragments unlike automatic interpretation which works on original image resolution. It is true that the ridge detection cannot distinguish between fracture, bedding planes, shadows etc. A priori knowledge can indeed help in removing false positives.

Reviewer Comment #5 5. Still the edges are detected when sharp on the topography. This is the condition for exhaustive tracking and possible comparison between worldwide remote outcrops. Pecularily, in carbonates long-lasting aerial exposure alters the colors, softens the fracture crests and smooth the reliefs. This is sometimes -but not always- related to karst genesis. A discussion on the limitations bias resulting from exposure conditions could be welcome.

Author's Response to Reviewer Comment #5 We have added the following sentences within the Discussion section (under Detection of large cavities and false positives) in the marked down manuscript to address this issue, "Additionally, carbonate outcrops are prone to widespread erosion owing to exposure to meteoric water from precipitation cycles and air corrosion. Geomorphological features owing to these effects may also play a role in generation of false positives."

Reviewer Comment #6 Fig. 11: indicate which one, between left and right, is manual and automated –

Author's Response We have added this detail to the Figure. The figure caption will be modified ("…automatic and manual.." changed to "…manual and automatic") to avoid confusion to the reader. ———————————————————————————- References Nyberg B, Nixon CW, Sanderson DJ (2018), Network GT: A GIS tool for geometric and topological analysis of two-dimensional networks, Geosphere, 14(4), doi:10.1130/GES01595.1

Cordonnier, J-B nad Loukas A (2019), Extrapolating Paths with Graph Neural Networks, CoRR, abs/1903.07518, http:..arxiv.org/abs/1903.07518

Hardebol NJ, Maier C, Nick H, Geiger S, Bertotti G, Boro H (2015), Multiscale fracture network characterization and impact on flow: A case study on the Latemar carbonate platform, Journal of Geophysical Research - Solid Earth, 120(12), https://doi.org/10.1002/2015JB011879

Lamarche J, Chabani A, Gauther BDM (2018), Dimensional threshold for fracture linking and hooking, Journal of Structural Geology, Vol 108, 171-179, https://doi.org/10.1016/j.jsg.2017.11.016

Interactive comment on Solid Earth Discuss., https://doi.org/10.5194/se-2019-104, 2019.

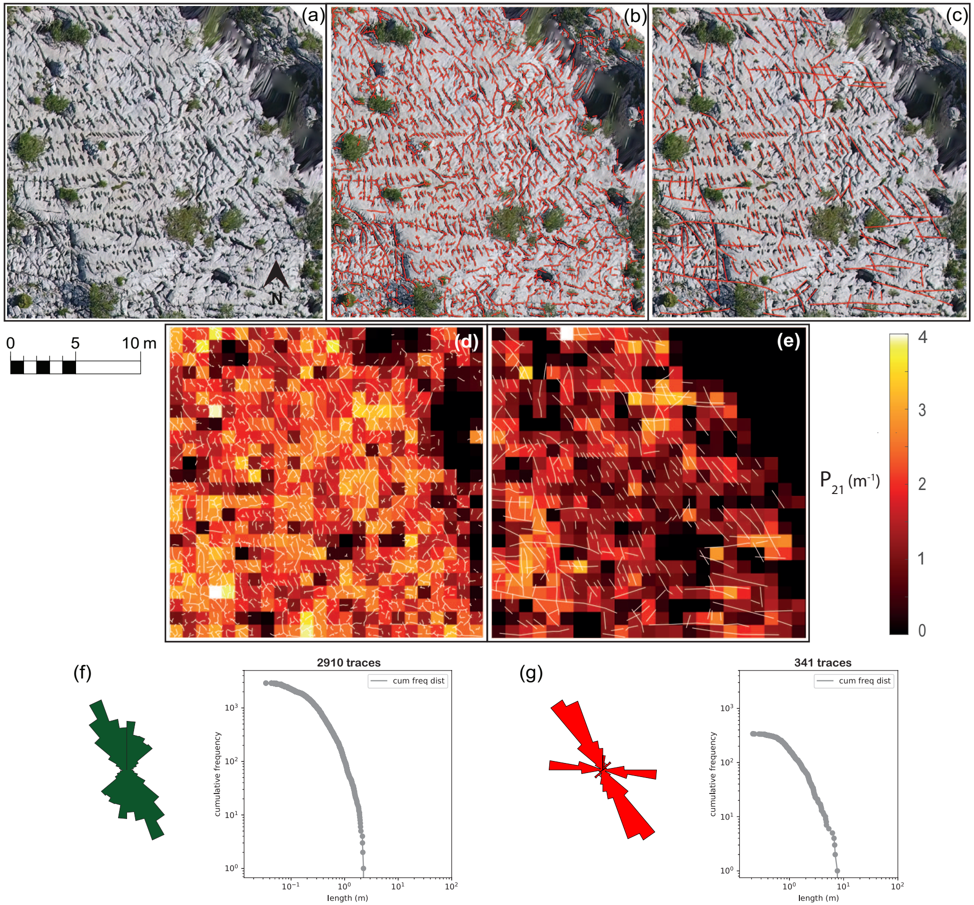

Fig. 1. Parmelan Automatic vs Manual Interpretation Comparison

Printer-friendly version

Discussion paper

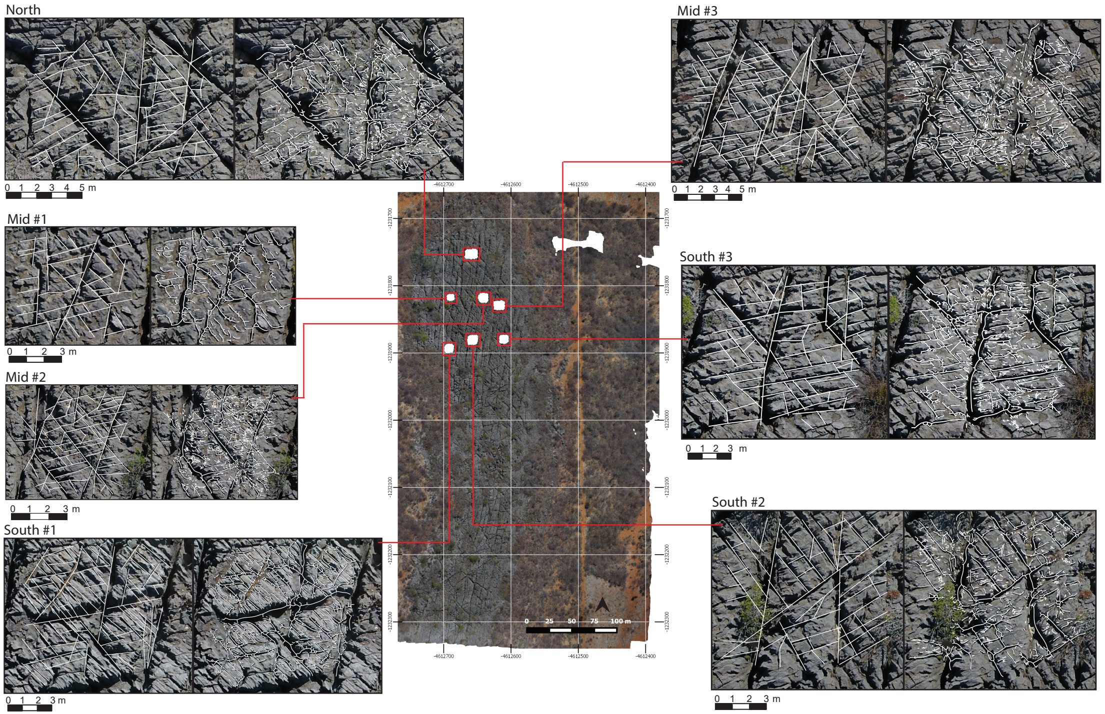

Fig. 2. Brejoes Manual vs Automatic Interpretation Comparison

Printer-friendly version

Discussion paper

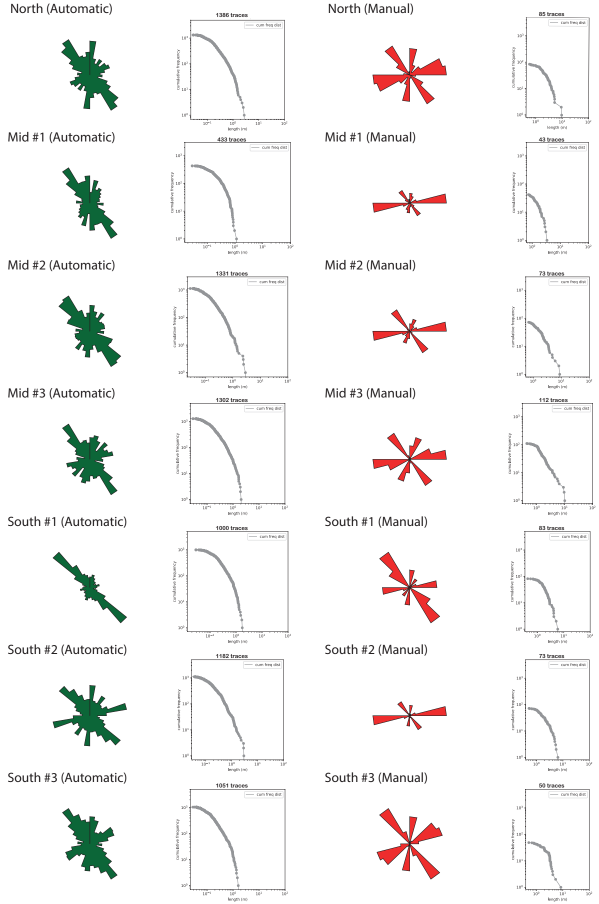

Fig. 3. Brejoes Rose Plots and Cumulative Length Distributions

Interactive comment

Printer-friendly version

Discussion paper

SED

Interactive comment

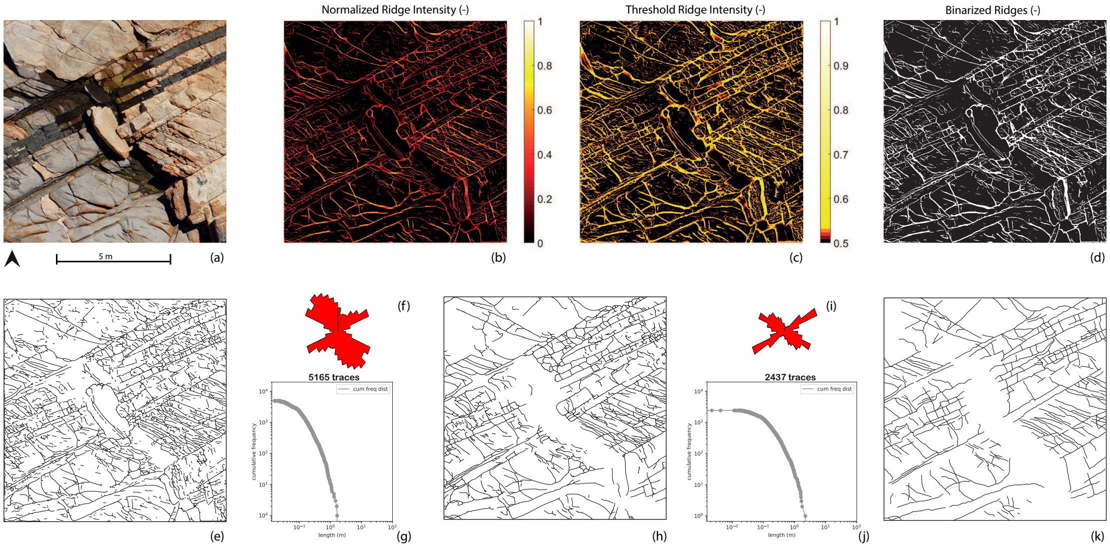

Fig. 4. Bingie Bingie 1 Results

Printer-friendly version

Discussion paper

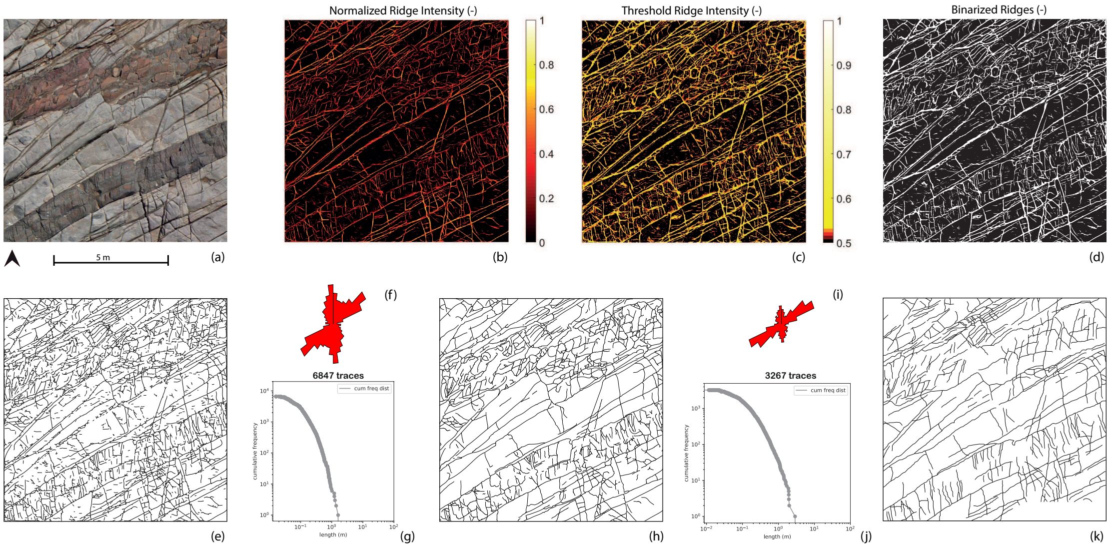

Fig. 5. Bingie Bingie 2 Results