DETECTING GRAIN BOUNDARIES IN DEFORMED ROCKS USING CELLULAR AUTOMATA APPROACH (MR41A-1850)

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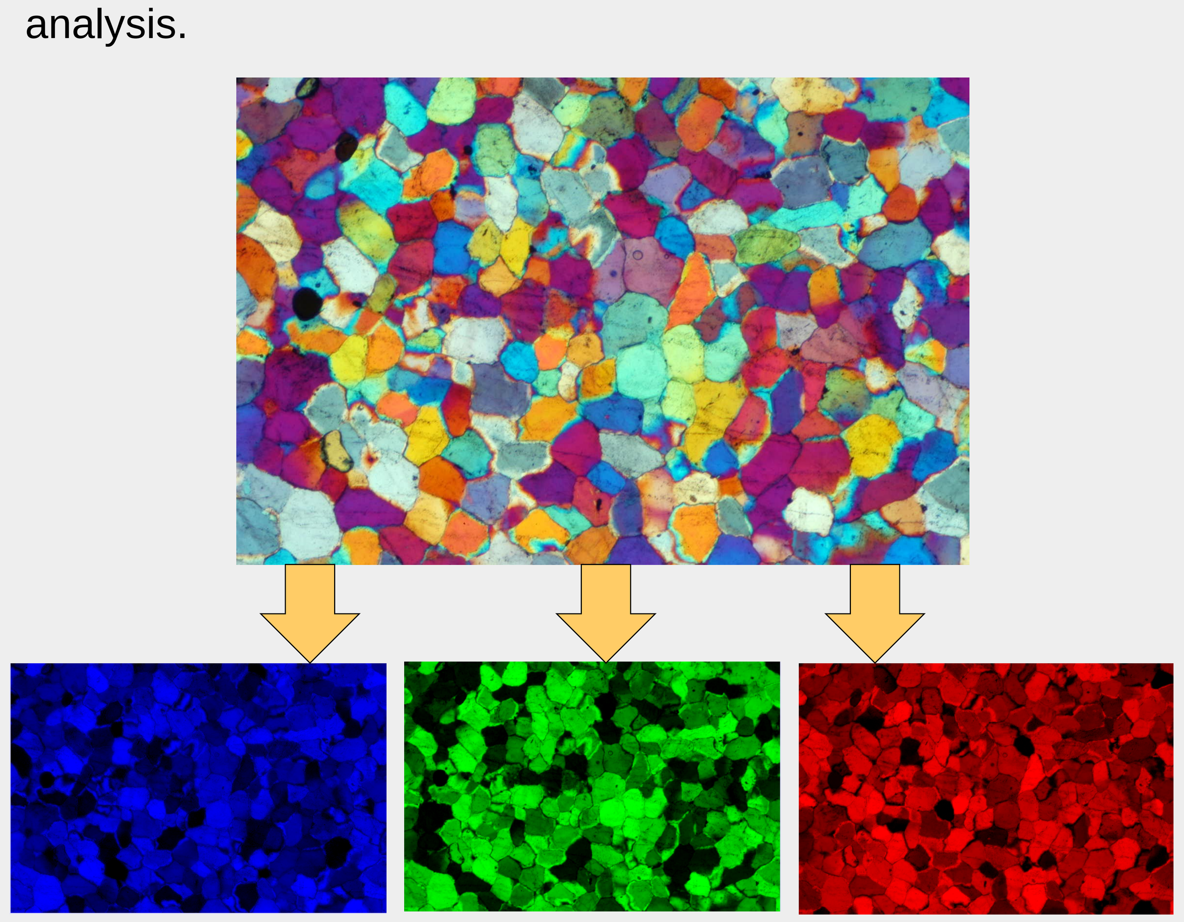
Abstract

Cellular automata (CA) are widely used and applied in geospatial dynamic modeling and image processing. Here, we explore the application of two-dimensional cellular automata to the problem of grain boundary detection in digital images of thin-sections from deformed rocks. The automated extraction of boundaries, which contain rich sources of information such as shape, orientation, and spatial distribution of grains involve a CA Moore neighborhood-based rules approach. The Moore neighborhood is 3 x 3 matrix that is used for changing states by comparing differences between a central pixel and its neighbors. In this dynamic approach, the future state of a pixel depends upon its current state and that of its neighbors. The rules that are used determine the future state of each cell (i.e., dead or alive) while the number of iterations to simulate boundaries detection are specified by the user. Each iteration outputs different detection scenarios of grain boundaries that can be evaluated and assessed for accuracy. The value of this proposed method will be compared against traditional a manual digitization approach and a recent GIS-based method developed for this purpose.

Materials

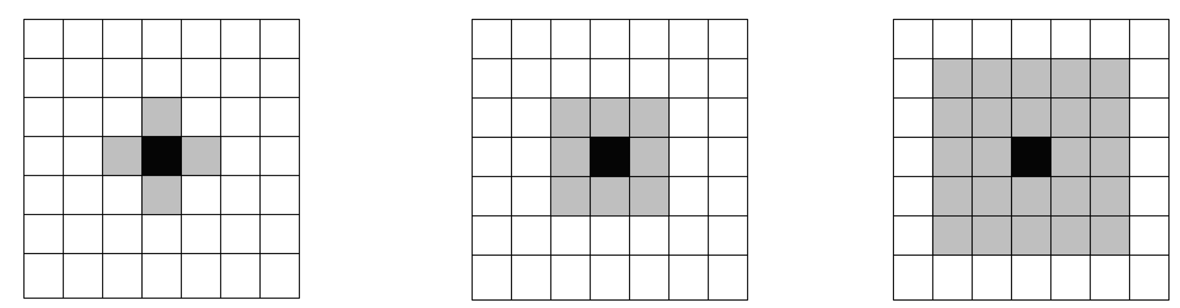
Blue, green and red bands extracted from a thin section color image (gypsum plate inserted) are used for the automated extraction of reproducible grain boundaries using edge detection analysis.



Blue Band Green Band Red Band

Methods

Cellular Automatas (CA) resemble similarity to partial differential equations, but are discrete systems with an ability to describe continuous dynamic systems. CA's consider space, time and automaton properties that have a finite and countable number of states. In this study the properties of the CA are based on a regular two-dimensional lattice where each cell of the lattice has a discrete state while the dynamic behavior is described by *neighboring* rules that govern the state of the cells through time. Examples of two-dimensional CA's with a square shaped neighborhood surrounding the central cell (x_0, y_0) are defined as von Neumann neighborhood, Moore's neighborhood, and extended Moore's neighborhood.



von Neumann 's Neighborhood | Moore's Neighborhood | Extended Moore's Neighborhood

The cellular automaton is represented by four elements A=(X,S,N,δ)

where X is the m dimensional space of each cell x=(x_1, x_2, x_3, .., x_m)

S is a nonempty finite set where cells can take only one state at any time from a set of states

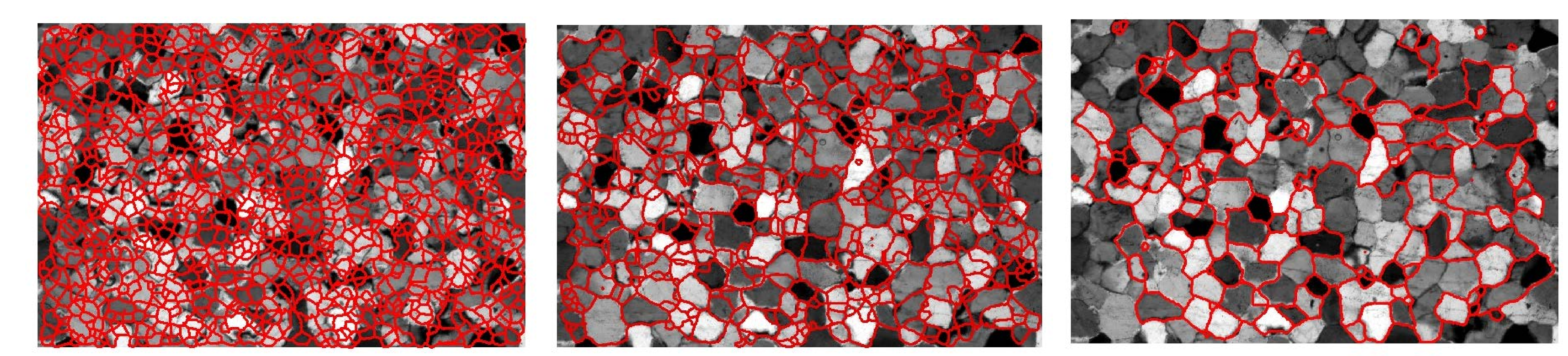
N is the neighborhood where the state of any cell depends on the states of other cells in the neighborhood

δ is the state transition function rule

Edge Detection

Applying the Moore's neighborhood

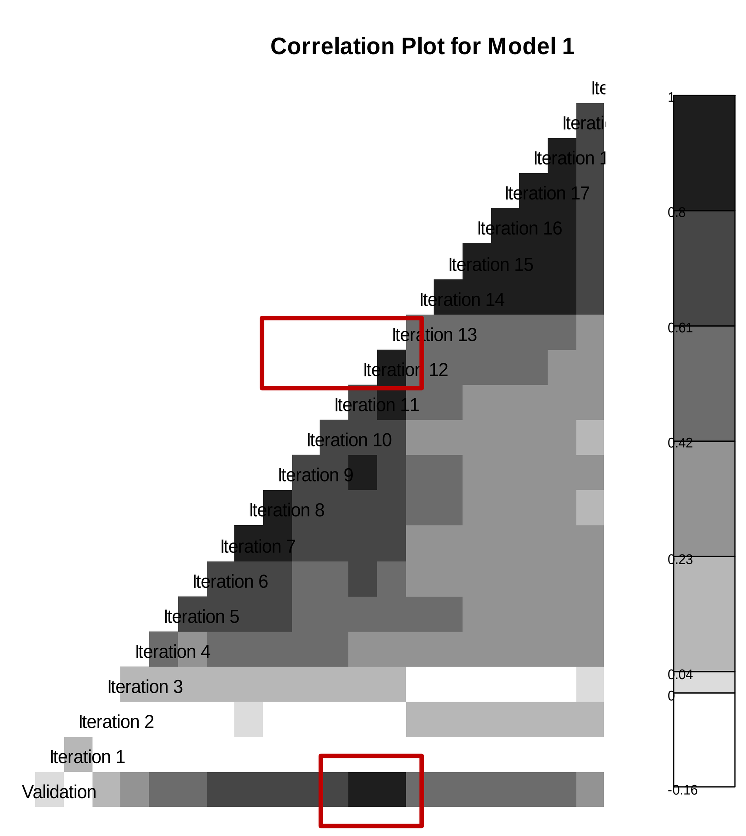
Set the threshold for comparison of color differences between neighbors and iterations
For each iteration
{
For every cell in each band
{
If the color difference between x_0, y_0 and its neighbors is greater that the threshold keep the state of the cell unchanged
}
Apply edge detection rules (i.e., more than three connected cells)
Move to the next state
}



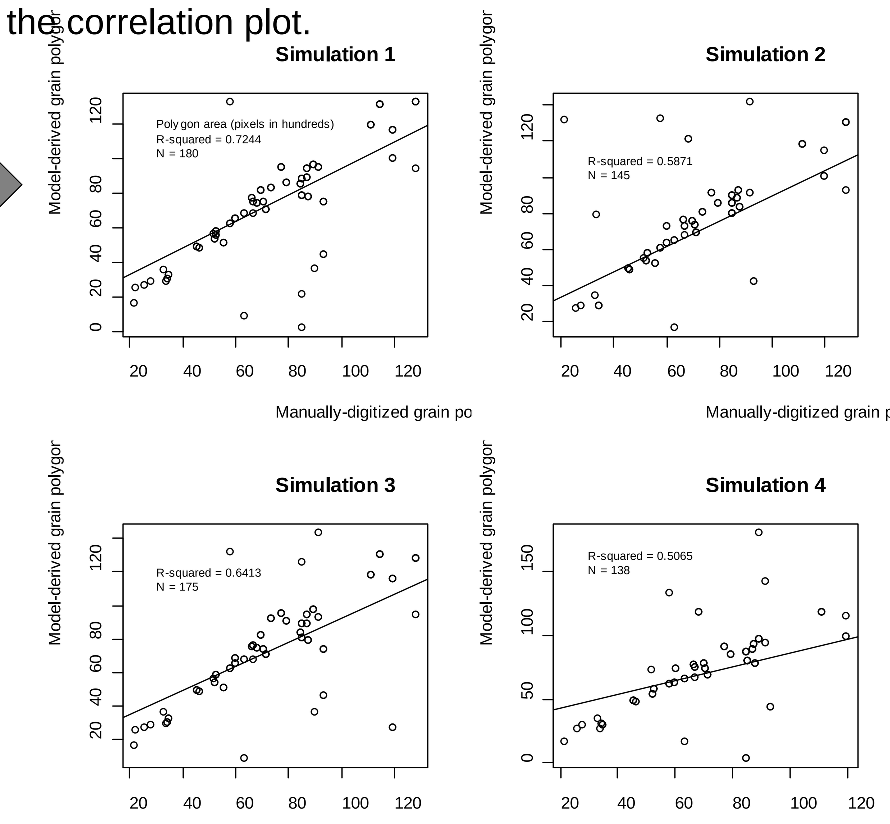
Iteration 3 | Iteration 5 | Iteration 17

Results and comparison with manual-digitized grain boundaries

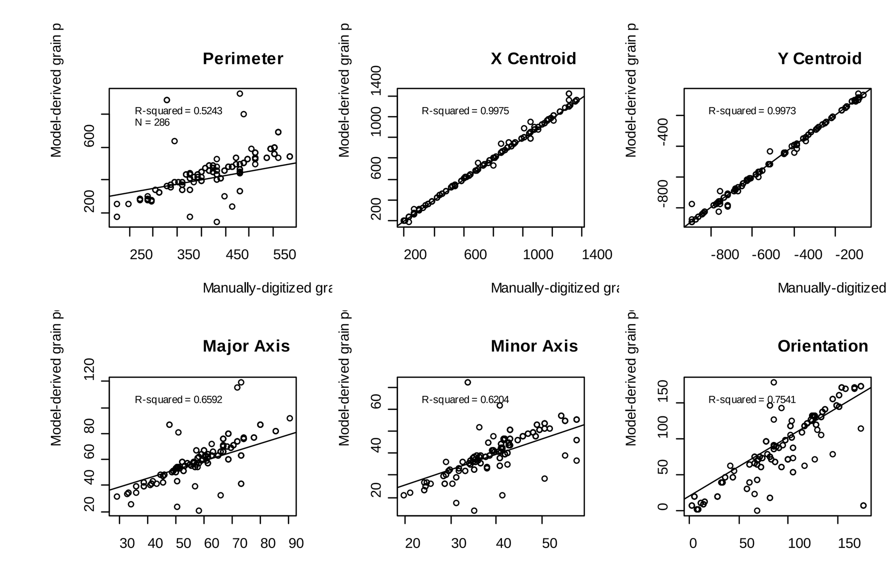
The correlation plot shows that manually-digitized grain boundaries have the highest correlation with Iterations 12 and 13 from the CA simulation.



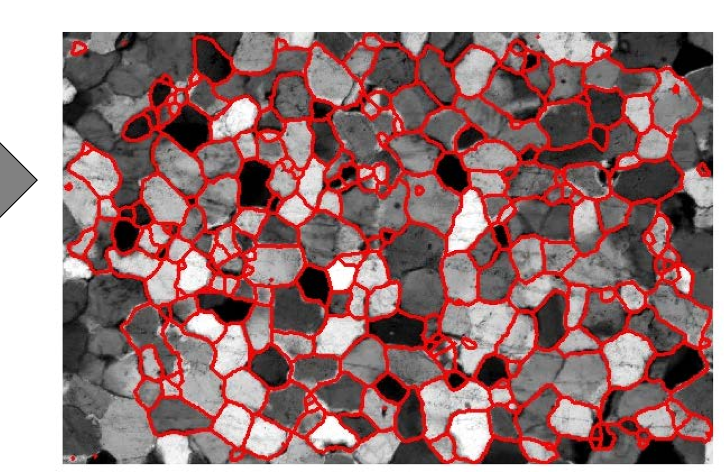
Different detection rules can yield different boundary patterns. The figure below shows the best relationships extracted from four simulations which applied different detection rules. For instance the first plot (Simulation 1) represents Iteration 12 from the correlation plot.



The figure further explores the geometry of the model-derived grains to the hand-digitized grains associated with Simulation 1. All the parameters show high correlations, but the highest is associated with the X and Y centroids.



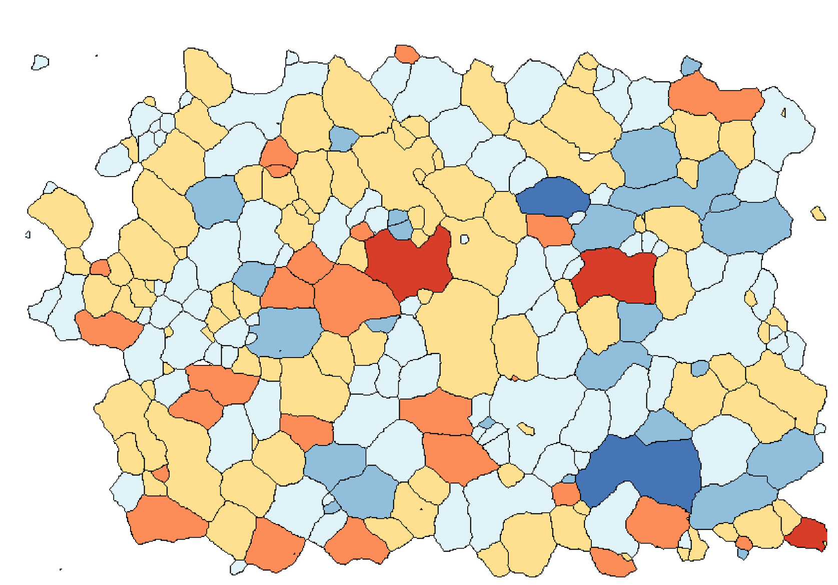
Automated extraction of reproducible grain boundary through edge detection analysis.

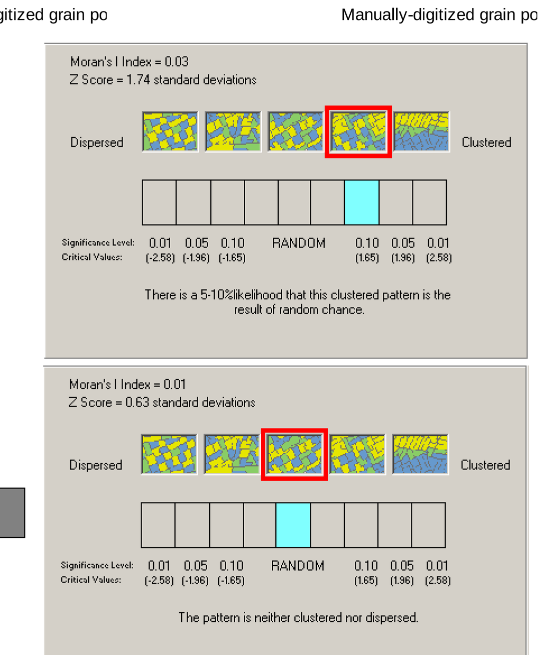


The *Orientation* of the polygons shows no spatial autocorrelation which indicates a random pattern.

Percentile: ORIENTATION

- < 1% (2)
- 1% - 10% (25)
- 10% - 50% (92)
- 50% - 90% (124)
- 90% - 99% (25)
- >99% (3)

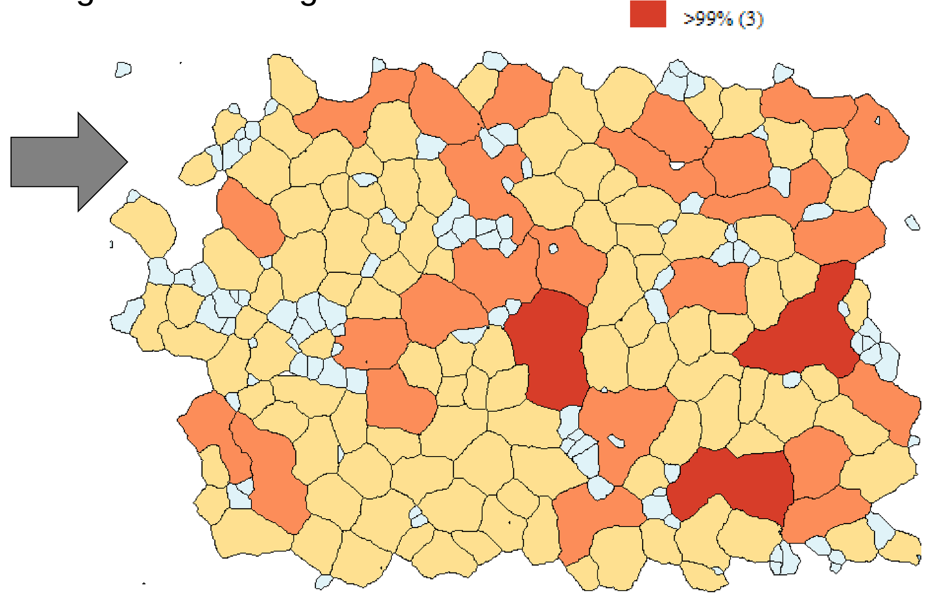




The *Area* of the polygons shows positive spatial autocorrelation which indicates the presence of grain clustering.

Percentile: AREA

- < 1% (0)
- 1% - 10% (27)
- 10% - 50% (108)
- 50% - 90% (108)
- 90% - 99% (25)
- >99% (3)



The scatter plots suggest some spatial differences in the slope of the regression of Orientation on Area across the image.