Cellular Automata Methods for Improved Edge Detection in Hyperspectral Imagery

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ABSTRACT:

Hyperspectral sensors are especially useful in classifying targets because the large number and distribution of spectral bands provides information regarding the material composition of the targets [1]. However, in situations where the spectrum of the target is not easily distinguishable from background spectrums, spectral based features may not be enough to identify the target from the background. This can be caused by noise (such as atmospheric or sensor noise) and situations where background object have nearly identical spectral signatures, which results in a high number of false positives or false negatives depending on where the decision boundary is placed. In these situations, features that are based on object morphology might be more useful.

In order to extract morphological features, objects must be extracted from the image. Often extracting objects from images involves detecting the edges of objects. Edge detection in gray scale images is well understood and described in [2]. Generally, edges are first detected by a high pass filter such as Roberts, Prewitt, or Sobel, and then edge fragments are connected together. It is desirable to have edges that are one pixel wide, that are located on the most probable location of the edge, and that are complete. Often this is done using morphological operators [3]. These processes become more complicated and less understood as we add more and more bands. There are no widely accepted edge detection methods specifically for hyperspectral images that take advantage of (or even account for) the hundreds or perhaps thousands of bands. This makes edge detection in hyperspectral imagery an extremely challenging task.

This article proposes using Cellular Automata (CAs) and adapted multispectral edge detection algorithms for hyperspectral imagery. An in depth description of CAs can be found in

[4]. CAs have several advantages derived from the fact that cells can communicate with their neighbors by changing states, and that they can contain complex finite state machines that can interpret their inputs. Often the finite state machines are simple enough that they can be implemented in programmable hardware such as FPGAs, which allows them to be evaluated very quickly. These advantageous properties of CAs have not been fully exploited for the purposes of edge detection and in particular have not been applied to high dimensional problems such as hyperspectral edge detection.

The CA used in this paper is a two-dimensional grid with the same dimensions as the image being analyzed and contains only 8 states. The generalized concept of the proposed CA hyperspectral edge detection methods works by implementing the following steps in order:

1. A standard edge detection algorithm adapted for a hyperspectral image.
2. Adaptive thresholding via CAs.
3. Edge connection via CAs.
4. Edge erosion via CAs.

The result of the CA is an edge map where edges of different intensities are represented and all edges are one pixel wide.

Figure 1 shows preliminary results, where the proposed CA method is compared to a more conventional Prewitt edge detector. The generalized method proposed above was implemented specifically in the following manner to achieve the results shown in Figure 1:

1. Utilize a Prewitt edge detector adapted for a hyperspectral image by computing spectral distance between pixels within a spatial neighborhood (N) to measure hyperspectral gradient.
2. Conduct localized threshold optimization implemented via CA with a 3-by-3 neighborhood around each CA cell.
3. Pixels greater than adaptive threshold seed a region growing process, where growth is linear in the direction perpendicular to maximum gradient, implemented via CA.
4. Erode edges by removing CA cells with the lowest gradient without breaking edge continuity.

Typically, a challenge with conventional edge detectors, such as Prewitt, Sobel, etc, is the selection of the threshold parameter. Figure 1 shows results of Prewitt method with varying thresholds. Regardless of threshold parameter optimization, the proposed CA method consistently performed better. For example, the CA method detected subtle edges while not becoming over saturated. The results in Figure 1 are representative of the wider set of results obtained by the authors. The full conference paper will provide full details of the CA algorithm and additional experimental results for more comparison methods and test imagery.

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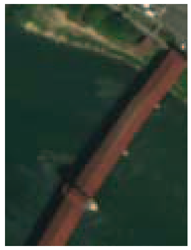
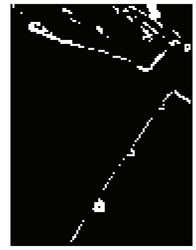
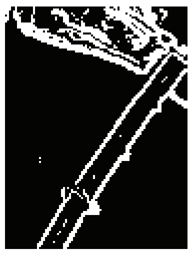


A.



B.



C.

D.

E.

F.

G.

H.

Figure 1. The RGB component of a hyperspectral image (A), and results of the CA (H) and a Prewitt edge detector with a range of thresholds (B-G). The bands were combined in the Prewitt edge detector by summing the independent results for the bands.
Image (A) courtesy of [5].