Recursive Hierarchical Image Segmentation by Region Growing and Constrained Spectral Clustering

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What is Hierarchical Image Segmentation?

A hierarchical image segmentation is a set of several image segmentations at different levels of segmentation detail in which the segmentations at coarser levels of detail can be produced from simple merges of regions from segmentations at finer levels of detail.

What is Hierarchical Image Segmentation? (cont'd)

A unique feature of hierarchical image segmentation is that the segmented region boundaries are maintained at the full image spatial resolution at all levels of the segmentation hierarchy.

Image Segmentation Overview

Approach	Problem
Spectral Feature Clustering	Spatial Information not Utilized
Edge Detection	No Guarantee of Closed Connected Regions
Region Growing	Global Convergence Difficult and Computationally Intensive

Image Segmentation Overview (cont'd)

Determining the mathematically optimal image segmentation for a given level of detail or number of regions is not possible due to computational constraints.

The most widely used definition of image segmentation by region growing avoids an concept of optimality and just accepts any segmentation that satisfies a specified criterion.

Image Segmentation Overview (cont'd)

Let $\boldsymbol{X}$ be a two-dimensional array representing an image. A segmentation of $\boldsymbol{X}$ can be defined as a partition of $\boldsymbol{X}$ into disjoint subsets $\boldsymbol{X}_1$, $\boldsymbol{X}_2$, …, $\boldsymbol{X}_N$, such that

1) $\bigcup_{i=1}^{N} X_i = X$
2) $X_i, i = 1,2,\ldots,N$ is connected
3) $\mathrm{P}(X_i) = \mathrm{TRUE}$ for $i = 1,2,\ldots,N$ and
4) $\mathrm{P}(X_i \bigcup X_j) = \mathrm{FALSE}$ for $i \neq j$, where $\boldsymbol{X}_{\mathrm{i}}$ and $\boldsymbol{X}_{\mathrm{j}}$ are adjacent.

Image Segmentation Overview (cont'd)

P($\boldsymbol{X}_i$) is a logical predicate that assigns the value TRUE or FALSE to $\boldsymbol{X}_i$, depending on the image data values in $\boldsymbol{X}_i$.

For example, let $\mathrm{P}(X_i) = \left(\frac{1}{n_i} \sum_{x_j \in X_i} \left\| x_j - \overline{x_i} \right\|_2 \leq T \right)$,

where n_i is the number of pixels in region i, $\overline{x_i}$ is the mean vector for region i, and T is a threshold.

Call this the "classical" definition of image segmentation by region growing (this definition, taken from Horowitz and Pavlidis, 1974, is used widely in the image segmentation literature).

Image Segmentation Overview (cont'd)

An ideal definition of image segmentation would be as follows:

Let $\boldsymbol{X}$ be a two-dimensional array representing an image. An ideal segmentation of $\boldsymbol{X}$ can be defined as a partition of $\boldsymbol{X}$ into disjoint subsets $\boldsymbol{X}_1$, $\boldsymbol{X}_2$, …, $\boldsymbol{X}_N$, such that

1) $\bigcup_{i=1}^{N} X_i = X$

2) $X_i, i = 1,2,\ldots,N$ is connected

Image Segmentation Overview (cont'd)

3) $\sum_{i=1}^{N} \mathrm{G}(X_i) = MINIMUM$ over all partitions into N regions and

4) $\mathrm{G}\left(X_i \bigcup X_j\right) > \mathrm{G}(X_i) + \mathrm{G}\left(X_j\right)$ for $i \neq j$, where $\boldsymbol{X}_\mathrm{i}$ and $\boldsymbol{X}_\mathrm{j}$ are adjacent.

Image Segmentation Overview (cont'd)

G($\boldsymbol{X}_i$) is a function that assigns a cost to partition $\boldsymbol{X}_i$, depending on the image data values in $\boldsymbol{X}_i$.

For example, let $G(X_i) = \left(\frac{1}{n_i} \sum_{x_j \in X_i} \left\| x_j - \overline{x_i} \right\|_2 \right)$,

where n_i is the number of pixels in region i, and $\overline{x_i}$ is the mean vector for region i.

Too computationally intensive to be practical.

Image Segmentation Overview (cont'd)

Hierarchical Step-Wise Optimal Segmentation (Beaulieu and Goldberg, 1989) or Iterative Parallel Region Growing (Tilton and Cox, 1983) is essentially a compromise between "classical" image segmentation and the ideal image segmentation.

The definition of image segmentation as followed by the Hierarchical Step-Wise Optimal (HSWO) segmentation algorithm given on the next slides.

Image Segmentation Overview (cont'd)

Let $\boldsymbol{X}$ be a two-dimensional array representing an image. A segmentation of $\boldsymbol{X}$ can be defined as a partition of $\boldsymbol{X}$ into disjoint subsets $\boldsymbol{X}_1$, $\boldsymbol{X}_2$, …, $\boldsymbol{X}_N$, such that

1) $\bigcup_{i=1}^{N} X_i = X$ and

2) $X_i, i = 1,2,\ldots,N$ is connected.

Image Segmentation Overview (cont'd)

Let $\mathrm{G}(\boldsymbol{X}_i)$ be a function that assigns a cost to partition $\boldsymbol{X}_i$, depending on the image data values in $\boldsymbol{X}_i$. Reorder the partition $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_{N-1}, \boldsymbol{X}_N$ such that:

$\mathrm{G}\left(X_{N-1} \bigcup X_N\right) \leq \mathrm{G}\left(X_i \bigcup X_j\right)$ for all $i \neq j$ where $\boldsymbol{X}_{N-1}$ and $\boldsymbol{X}_N$ are adjacent and $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ are adjacent. The segmentation of $\boldsymbol{X}$ into N-1 regions is defined as the partition $X_1', X_2', \ldots, X_{N-1}'$ where $X_i' = X_i$ for $i = 1, 2, \ldots, N-2$ and $X_{N-1}' = X_{N-1} \bigcup X_N$.

Hierarchical Segmentation (HSEG)

HSEG is the same as HSWO, except that HSEG optionally alternates merges of spatially adjacent regions with merges spatially non-adjacent regions.

In addition, HSEG also offers a wide choice of cost functions. Currently implemented are cost functions based on vector norms (1-norm, 2-norm and infinity-norm), and mean squared error. Other cost functions can be implemented (e.g. statistical hypothesis testing, constraining image entropy, normalized vector distance, and others).

Hierarchical Segmentation (cont'd)

As with all region growing approaches to image segmentation, HSEG must address the problem of global convergence, i. e. when to stop growing regions?

Instead of trying to solve the global convergence problem through determining one global stopping point, HSEG monitors a global dissimilarity criterion (cost function) and outputs a hierarchical set of image segmentations based on the dynamic behavior of this criterion.

Hierarchical Segmentation (cont'd)

For example, let $G_{global}(X) = \frac{1}{N}\left[\sum_{X_i \text{ in } X}\left(\sum_{x_j \in X_i}\left\| x_j - \overline{x_i}\right\|_2\right)\right]$,

where n_i is the number of pixels in region i, $\overline{x_i}$ is the mean vector for region i, and N is the total number of pixels in the image.

In HSEG, the segmentation result at iteration i-1 is saved as a hierarchical segmentation output when

$$\frac{G^{i}_{global}}{G^{i-1}_{global}} > threshold.$$

Hierarchical Segmentation (cont'd)

Algorithmic Description of HSEG:

- Give each data point a region label and set the global criterion value, *critval*, equal to zero. If a pre-segmentation is provided, label each data point according to the pre-segmentation. Otherwise, label each data point as a separate region.
- Calculate the dissimilarity criterion value, *dissim_val*, between each spatially adjacent region.
- Find the smallest *dissim_val* and set *thresh_val* equal to it. Then merge all pairs of spatially adjacent regions with *dissim_val* ≤ *thresh_val*.

Hierarchical Segmentation (cont'd)

4. If *spclust_wght* = 0.0, go to step 6. Otherwise, calculate the *dissim_val* between all pairs of non-spatially adjacent regions.
5. Merge all pairs of non-spatially adjacent regions with *dissim_val* ≤ *spclust_wght* thresh_val*.
6. If the number of regions remaining is less than the preset value *chk_nregions*, go to step 7. Otherwise, go to step 2.

Hierarchical Segmentation (cont'd)

7. Let *prevcritval* = *critval*. Calculate the current global criterion value and set *critval* equal to this value. If *prevcritval* = zero, go to step 2. Otherwise calculate *cvratio* = *critval/prevcritval.* If *cvratio* is greater than the preset threshold *convfact*, save the region label map from the previous iteration as a "raw" segmentation result. Also, store the region number of pixels list, region mean vector list and region criterion value list for this previous iteration. (Note: The region criterion value is the portion of the global criterion value contributed by the data points covered by the region.) If the number of regions remaining is two or less, save the region information from the current iteration as the coarsest instance of the final hierarchical segmentation result and stop. Otherwise, go to step 2.

Hierarchical Segmentation (cont'd)

HSWO is computationally intensive and HSEG with non-adjacent region merging is even more computationally intensive (due a combinatorial explosion of required comparisons between regions).

The computational problem is solved through a recursive formulation of the HSEG algorithm.

Recursive Hierarchical Segmentation (RHSEG)

RHSEG recursively divides an image into quarter sections until the image sections are small enough where the combinatorial explosion of inter-region comparisons is sufficiently reduced (about 1000 to 4000 pixels).

HSEG is performed on each section until a preset number of regions is reached – and the recursion is returned up until the image is fully reassembled.

Described in NASA Case Number GSC 14,328-1.

Recursive Hierarchical Segmentation (RHSEG)

Algorithmic Description of RHSEG:

1. Specify the number of levels of recursion required (*rnb_levels*) and pad the input data set, if necessary, so the width and height of the data set can be evenly divided by $2^{rnb\_levels-1}$. (A good value for *rnb_levels* results in a data section at *level* = *rnb_levels* consisting of roughly 1000 to 4000 data points.) Set *level* = 1.
2. Call *recur_hseg(level,data)*.
3. Execute the HSEG algorithm using as a pre-segmentation the segmentation output by the call to *rhseg*() in step 2. (Continue executing HSEG past the point that the number of regions reaches *chk_nregions* and save the segmentation results as specified.)

Recursive Hierarchical Segmentation (RHSEG)

Outline of *recur_hseg(level,data)*.:

1. If *level* = *rnb_levels*, go to step 3. Otherwise, divide the data set into four equal subsections and call *recur_hseg(level+1,sub_data)* for each subsection of the data set (represented as *sub_data*).
2. After the calls to *recur_hseg( )* for each data set subsection from step 1 complete processing, reassemble the data segmentation results.
3. Execute the HSEG algorithm as described in the *HSEG Algorithm Description* above (using the reassembled segmentation results are as the pre-segmentation when *level* < *rnb_levels*), with the following modification: Terminate the algorithm when the number of regions reaches the preset value *min_nregions* (if *level* = 1, terminate at the greater of *min_nregions* or *chk_nregions*) and do not check for *critval* or output any "raw" segmentation results .

Recursive Hierarchical Segmentation (cont'd)

A fast parallel implementation of RHSEG as been devised and is described in NASA Case Number GSC 14,305-1 (and U. S. patent application no. 5,965,879).

A method for eliminating artifacts from the recursive subdivision and reassembly of the image is described in NASA Case Number GSC 14,681-1 (suggested for patent application). With this method, a step #4 is added to the *recur_hseg( )* definition, in which the region labels of selected image pixels are switched to a more similar region.

Spatial Feature

Any dissimilarity function can be augmented by a spatial feature, based on the region standard deviation, as follows:

If D is the dissimilarity function value before combination with the spatial feature value, the combined dissimilarity function value (comparing regions j and k), D^c, is:

$$D^c = D + spatial\_wght * \left| sf_j - sf_k \right|,$$

where sf_j and sf_k are the spatial feature values for regions j and k, respectively.

Spatial Feature (cont'd)

The spatial feature employed is the spectral band maximum region standard deviation. For regions consisting of 9 or more pixels, the region standard deviation for spectral band b is :

$$\sigma_b = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_{bi} - \bar{x}_b^2\right)} = \sqrt{\frac{1}{N-1}\left[\sum_{i=1}^{N} x_{bi}^2 - N\bar{x}_b^2\right]},$$

where N is the number of pixels in the region and $\bar{x}_b$ is the region mean for spectral band b:

$$\bar{x}_b = \frac{1}{N}\sum_{i=1}^{N} x_{bi}.$$

Spatial Feature (cont'd)

The region spatial feature value is then defined as:

$$\sigma = \max\{\sigma_b : b = 1,2,\ldots,B\}$$

where B is the number of spectral bands.

For regions consisting only 1 pixel, the maximum over bands of the minimum local standard deviation ($ml\sigma$) calculated over all possible 3x3 windows containing the pixel is used as a substitute for the band maximum region standard deviation.

Spatial Feature (cont'd)

For regions consisting of 2 up through 8 pixels, a weighted average of the band maximum minimum local standard deviation and the band maximum region standard deviation is substituted for the band maximum region standard deviation as shown on the next slide ->

Spatial Feature (cont'd)

2 pixel regions: $0.875 * ml\sigma + 0.125 * \sigma$

3 pixel regions: $0.75 * ml\sigma + 0.25 * \sigma$

4 pixel regions: $0.625 * ml\sigma + 0.375 * \sigma$

5 pixel regions: $0.50 * ml\sigma + 0.50 * \sigma$

6 pixel regions: $0.375 * ml\sigma + 0.625 * \sigma$

7 pixel regions: $0.25 * ml\sigma + 0.75 * \sigma$

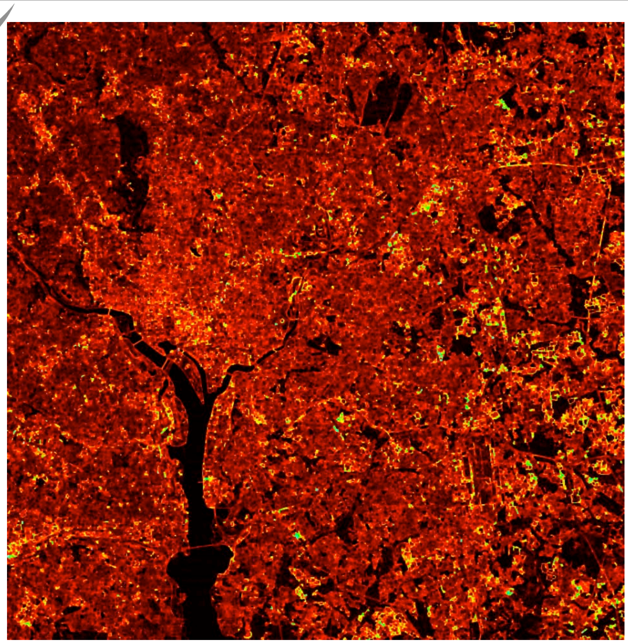
8 pixel regions: $0.125 * ml\sigma + 0.875 * \sigma$

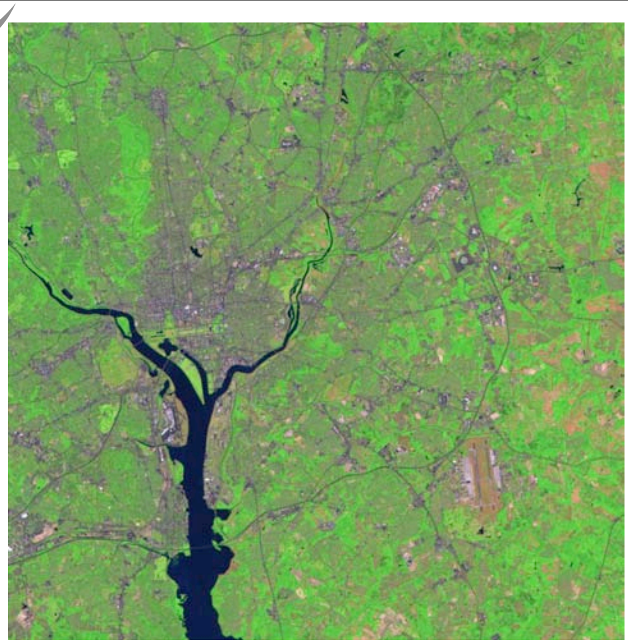
Example: Landsat Thematic Mapper data

A 1024x1024 pixel section of Landsat ETM+ data obtained on May 28, 1999 over Washington, DC, U.S.A.

Parameters: *spclust_wght* = 0.9, *spatial_wght* =1.0, *min_nregions* = 256, *chk_nregions* = 64.

Produced 12 hierarchical segmentation levels.





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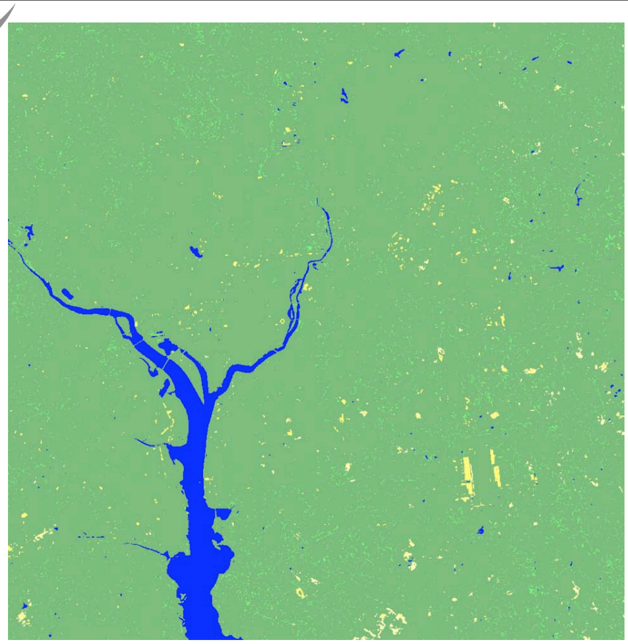

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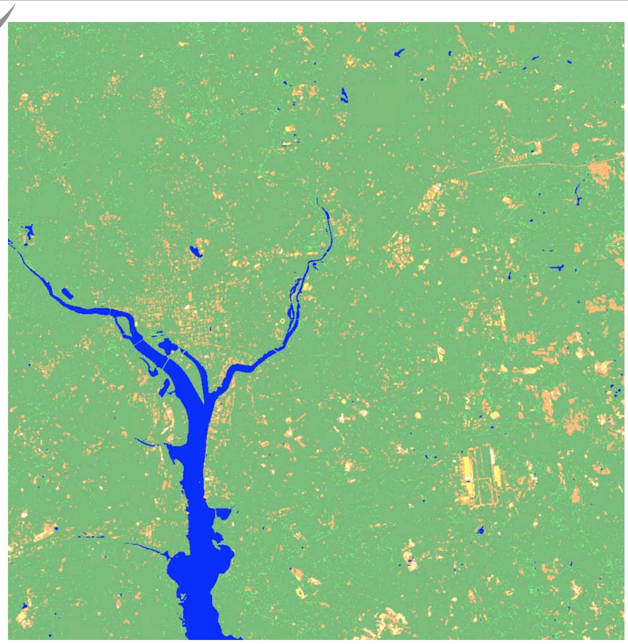

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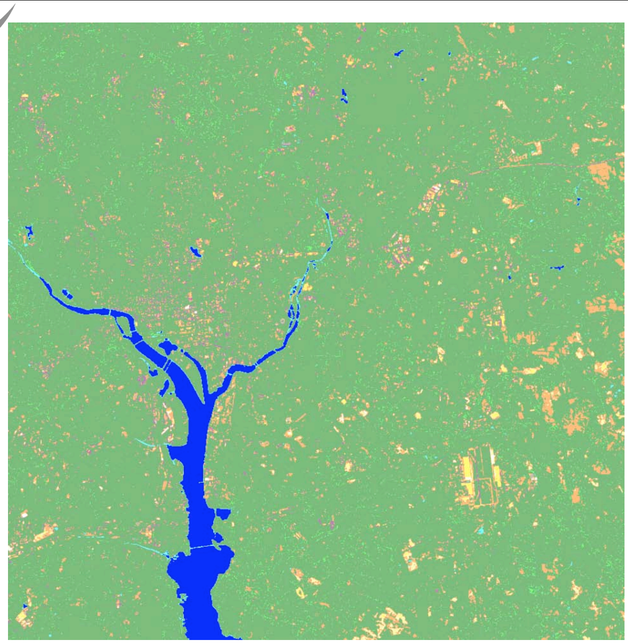

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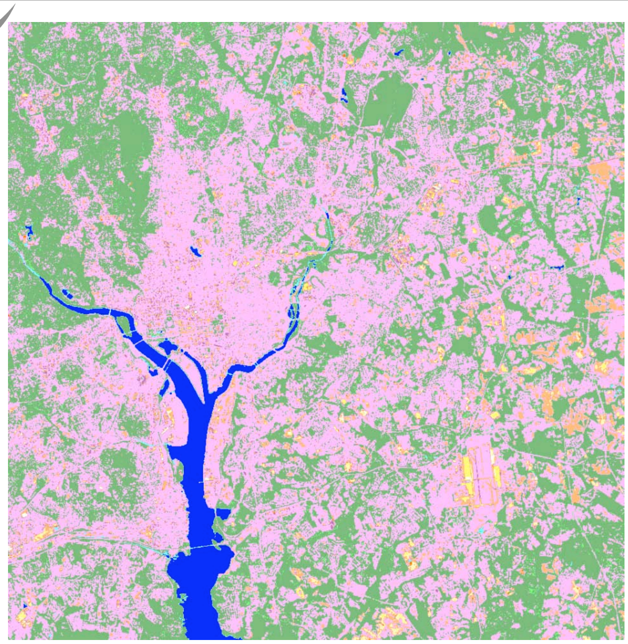

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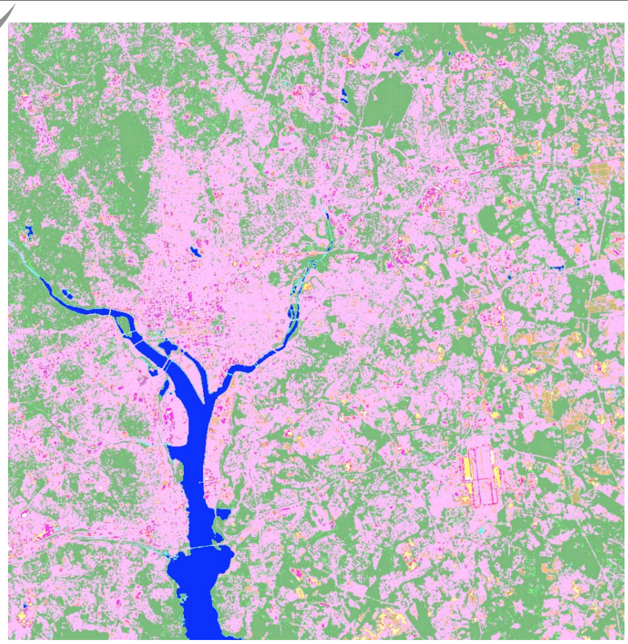

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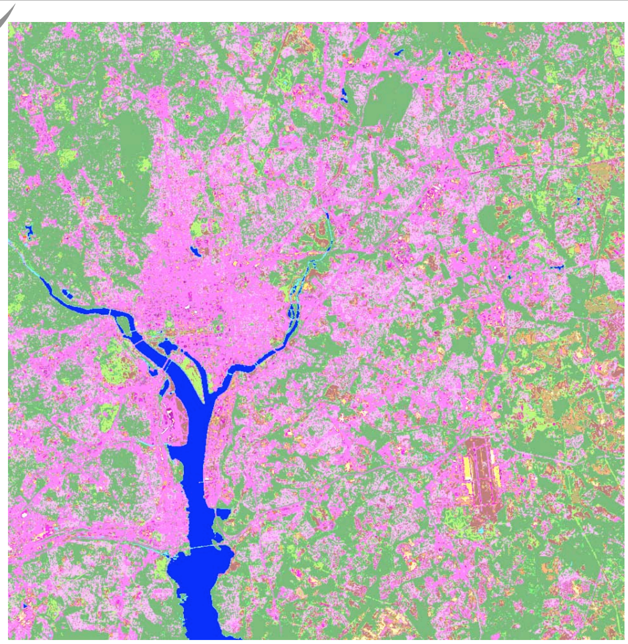

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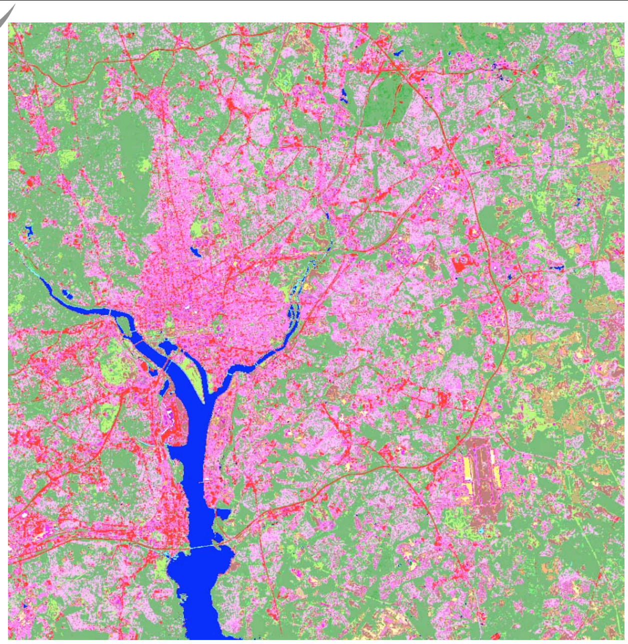

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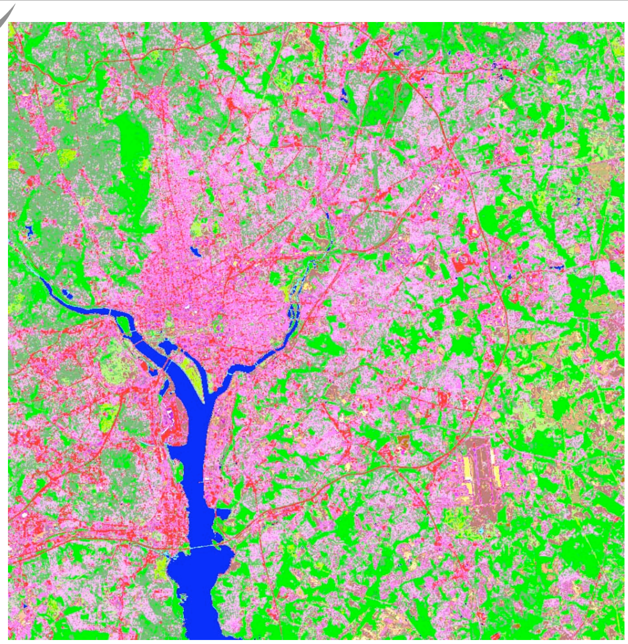

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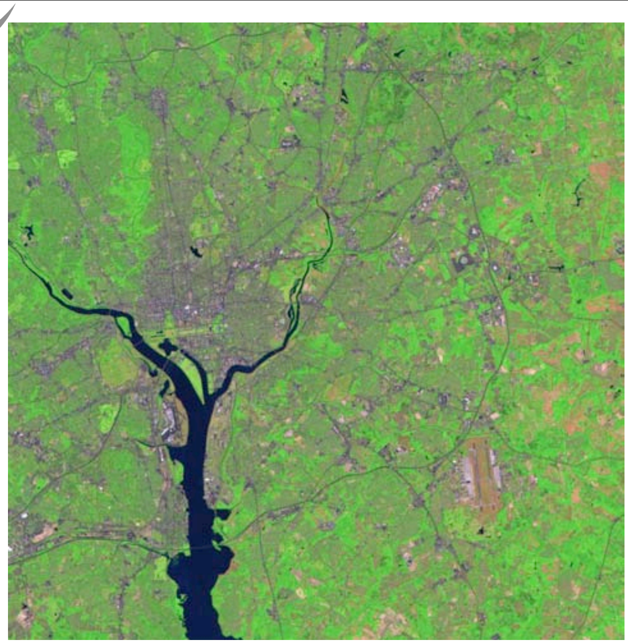
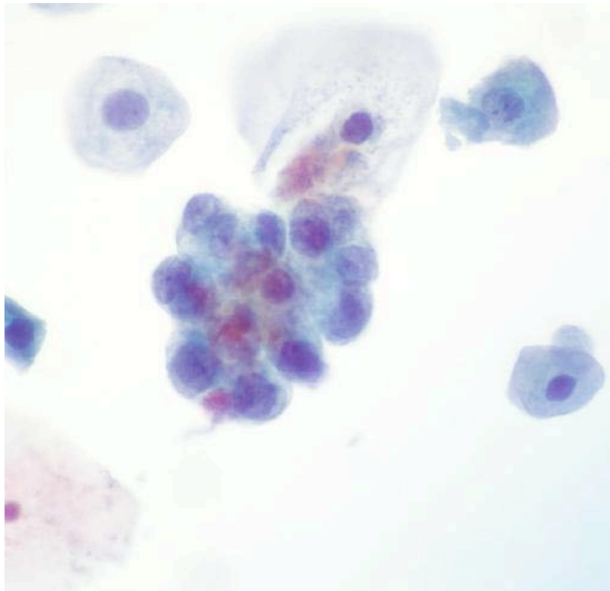


Interest from Medical Community

- Dr. Ron Summers, National Cancer Institute, NIH: Interested in applying 3-D version of HSEG/ RHSEG to his prototype system for finding pre-cancerous polyps in CAT scans of colons.
- Bartron Medical Imaging, LLC, is interested in incorporating RHSEG into their image management diagnostic system.



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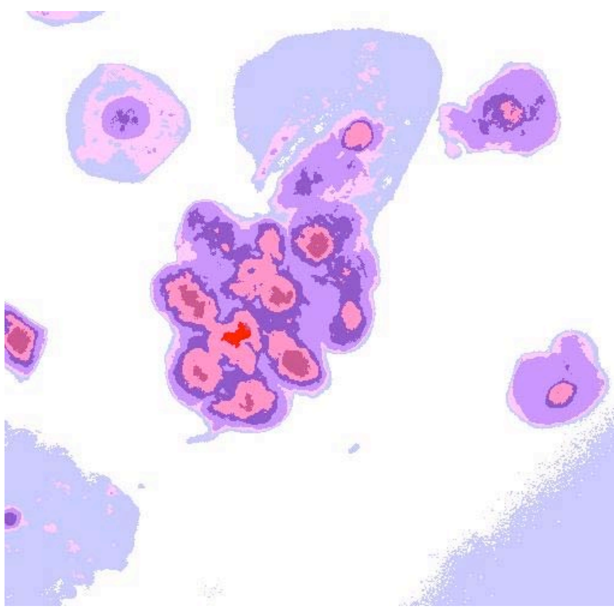

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Conference Proceedings Articles

[1] James C. Tilton, "Image segmentation by region growing and spectral clustering with a natural convergence criterion," *Proceedings of the 1998 International Geoscience and Remote Sensing Symposium*, Seattle, WA, July 6-10, 1998.

[2] James C. Tilton and William T. Lawrence, "Interactive analysis of hierarchical image segmentation," *Proc. of the 2000 International Geoscience and Remote Sensing Symposium*, Honolulu, HI, July 24-28, 2000.

[3] James C. Tilton, Giovanni Marchisio, Kryzstof Koperski and Mihai Datcu, "Image information mining utilizing hierarchical segmentation," *Proc. of the 2002 International Geoscience and Remote Sensing Symposium*, Toronto, CA, Vol. II, pp. 1029-1031, June 24-28, 2002.

Disclosures of Technology

[1] James C. Tilton, "Method for recursive implementation of hierarchical segmentation on parallel computers," *Disclosure of Invention and New Technology: NASA Case Number GSC 14,305-1*, February 2, 2000.

[2] James C. Tilton, "Method for recursive hierarchical segmentation by region growing and spectral clustering with a natural convergence criterion," *Disclosure of Invention and New Technology: NASA Case Number GSC 14,328-1*, February 28, 2000. See also http://code935.gsfc.nasa.gov/code935/tilton.

[3] James C. Tilton, "Method for recursive hierarchical segmentation which eliminates processing window artifacts," *Disclosure of Invention and New Technology: NASA Case No. GSC 14,681-1*, October 11, 2002.

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[1] S. L. Horowitz and T. Pavlidis, “Picture segmentation by a directed split-and-merge procedure,” *Proc. Second Int. Joint Conf. Pattern Recognition*, pp. 424-433, 1974.

[2] J. C. Tilton and S. C. Cox, “Segmentation of remotely sensed data using parallel region growing,” *Digest of the 1983 International Geoscience and Remote Sensing Symposium*, San Francisco, Ca, pp. 9.1-9.6, August 31 – September 2, 1983.

[3] J.-M. Beaulieu and M. Goldberg, “Hierarchy in picture segmentation: A stepwise optimization approach,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, pp. 150-163, Feb. 1989.