

# Knowledge Discovery and Data Mining Based on Hierarchical Segmentation of Image Data

James C. Tilton

NASA's Goddard Space Flight Center

Giovanni Marchisio

Insightful Corp. (aka. MathSoft)

Mihai Datcu

German Aerospace Center, DLR

# Goal & Technical Objectives

- To develop techniques for finding information and for discovering unexpected objects in imagery data through:
- Exploring the intrinsic region properties of regions in a segmentation hierarchy with the goal of developing heuristics for an automatic generic labeling of image regions, and
- The development of approaches for image information mining and knowledge discovery on image data represented as a segmentation hierarchy.

# Technical Problem Statement

We seek to exploit the unique characteristics of an image represented as a hierarchical segmentation for knowledge discovery and data mining.

Measures of region shapes and textures in particular levels of the segmentation hierarchy and how these measures vary at different levels of the segmentation hierarchy will be used to automatically obtain a generic labeling of the image.

Features based on the generic labeling of the image will be used as inputs to a data mining system (VisiMine).

# Technical Approach

- Detailed analysis of region properties embodied in a hierarchical image segmentation (HSEG).
- Development of semi-automatic and automatic labeling approaches for an image represented by a segmentation hierarchy.
- Integration of HSEG results with VisiMine (a data mining package).
- Data mining and knowledge discovery using the integration of HSEG with VisiMine.
- Development of Visual Grammar.
- Investigation of algorithms for hierarchical classification.
- The general integration of automatic generic region labeling with knowledge discovery and data mining.
- Comparison of HSEG with other segmentation approaches such as clustering by melting.

# Integration of HSEG with VisiMine

- The HSEG output stored as pixel level features together with the description of the hierarchy as a VisiMine model.
- The region and tile level features extracted based on pixel level attributes.
- The results accessible for all data mining tasks including similarity searches, classification and regression, and label training.

# Data mining and knowledge discovery

- The generic image labeling is searched for specific region types based on ancillary information from the area of interest. The regions searched based on spectral, textural and shape information.
- The regions classified based on trained models. Regions that can not be labeled into specified categories may indicate problems with the data (haze, clouds, etc.).
- Relevance feedback and feature selection used to find the best set of features and levels of HSEG information in combination with other features.

# Development of Visual Grammar

- Bayesian label training used for automatic identification of meaningful regions in images (e.g. city, residential, water, field, forest, glacier).
- Fuzzy modeling of region spatial relationships used to describe high-level user concepts (e.g. bordering, surrounding, near, far, above, below).
- Bayesian classifiers learn image classes based on automatic selection of distinguishing (e.g. frequently occurring, rarely occurring) relations between regions.

# Algorithms for hierarchical classification

- Insightful will improve the performance of classification algorithms with the introduction of:
  - Hidden Markov Models,
  - Decision trees and forests,
  - Boosted and bagged Bayesian classifiers.

# Integration of automatic generic region labeling with knowledge discovery and data mining

- Insightful will investigate automation of the labeling process by building the database of prior models based on ground truth.
- Hidden Markov Models and other statistical techniques will be used to model transition states between level in RHSEG.
- The initial labeling will be produced based on these models and a user will be able to further refine this labeling.

# Analysis of region properties embodied in hierarchical image segmentation and development of semi-automatic and automatic labeling approaches

- Minimal progress in this area (to be explored by NASA PI).
- NASA PI's efforts this past year have been concentrated a recently successful effort to refine the HSEG program to produce artifact free results with an object oriented C++ implementation using MPI software for parallelization.

# Processing Times for the new version of HSEG on NASA's HIVE2 Beowulf Cluster

Image Size (Landsat TM)	Processing Time (min:sec)	Number of Processors
0064x0064	00:06	4
0128x0128	00:25	16
0256x0256	01:37	64
0512x0512	08:50	64
1024x1024	10:37	64

# Comparison of HSEG with other segmentation approaches

- DLR Co-I has developed a method for “clustering by melting.”
- Results will be compared and contrasted with the segmentations produced with the NASA PI’s HSEG approach.

# Data and NASA Relevance

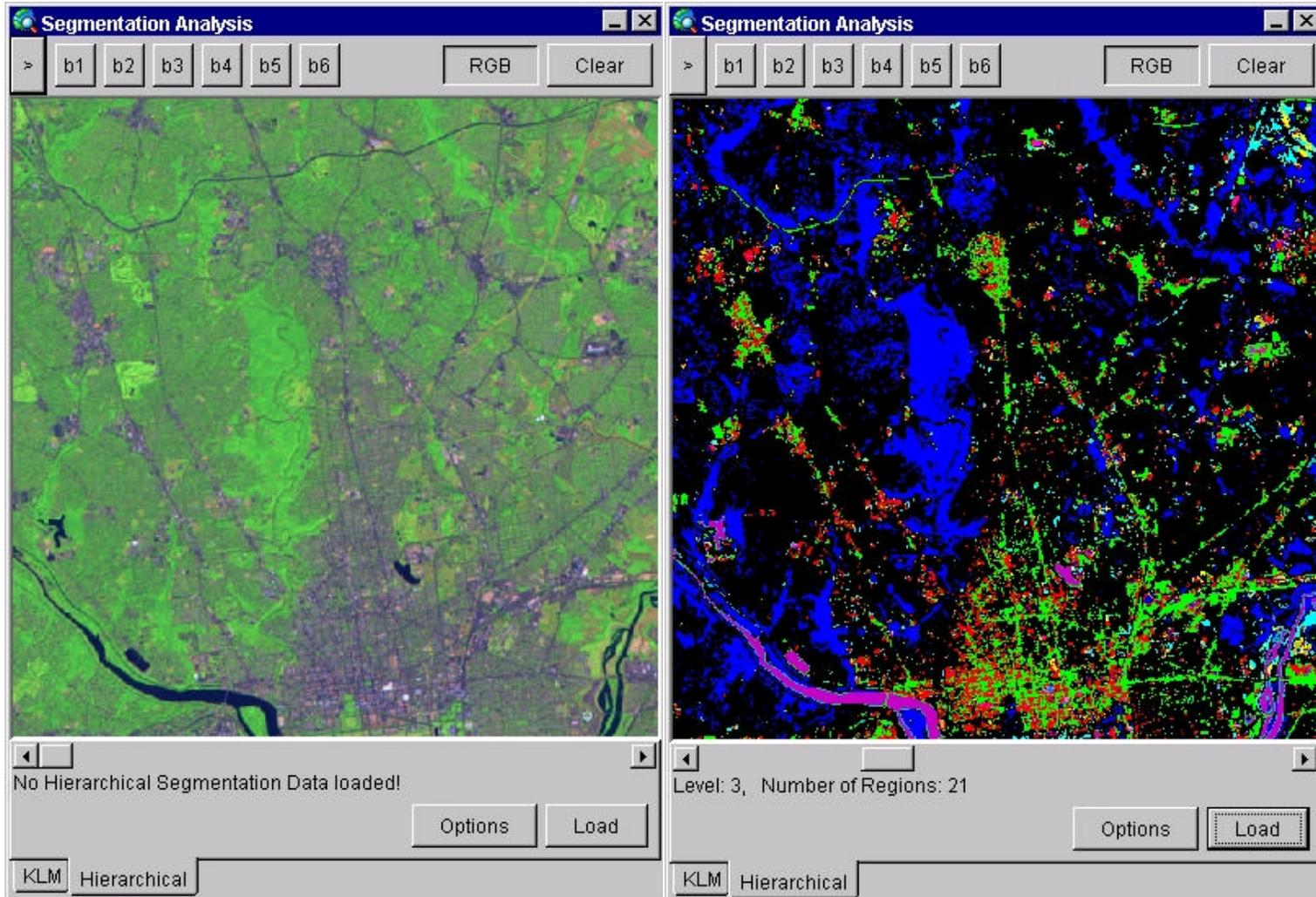
- Initial data sets include Landsat TM, X-SAR/SAR and IKONOS data.
- There is a great need for improved tools for automatically or semi-automatically extracting expected information and discovering new information from the numerous imagery data sets gathered from NASA's Earth and planetary viewing satellites.

# Accomplishments & Preliminary Findings

- In the first year of the project the following tasks were investigated:
  - Integration of the hierarchical segmentation algorithm output with VisiMine.
  - Data Mining and Knowledge Discovery using hierarchical segmentation algorithm results.
  - Development of Visual Grammar.

# Integration of hierarchical segmentation algorithm output with VisiMine

- The output of HSEG in the format provided by NASA was integrated with VisiMine.
- A user can select proper files using a GUI and the HSEG results are inserted to the database.
- The segmentation for each level can be stored in the format compatible with other features.
- A user can browse the changes of segmentation through different levels.
- The VisiMine Data Manager enables user friendly data manipulation.



Visualization of RHSEG results

# Data Mining and Knowledge Discovery using hierarchical segmentation algorithm results

- We performed preliminary evaluation of Data Mining results based on HSEG results.
- The precision of similarity searches based on HSEG is superior in the comparison with searches based on other features.
- The development of automated feature selection and level selection should enable the selection of best levels for similarity searches.

Precision curves for CLARA features and

---

A combination of HSEG features with Gabor texture features

Precision curves for HSEG features on different hierarchy level

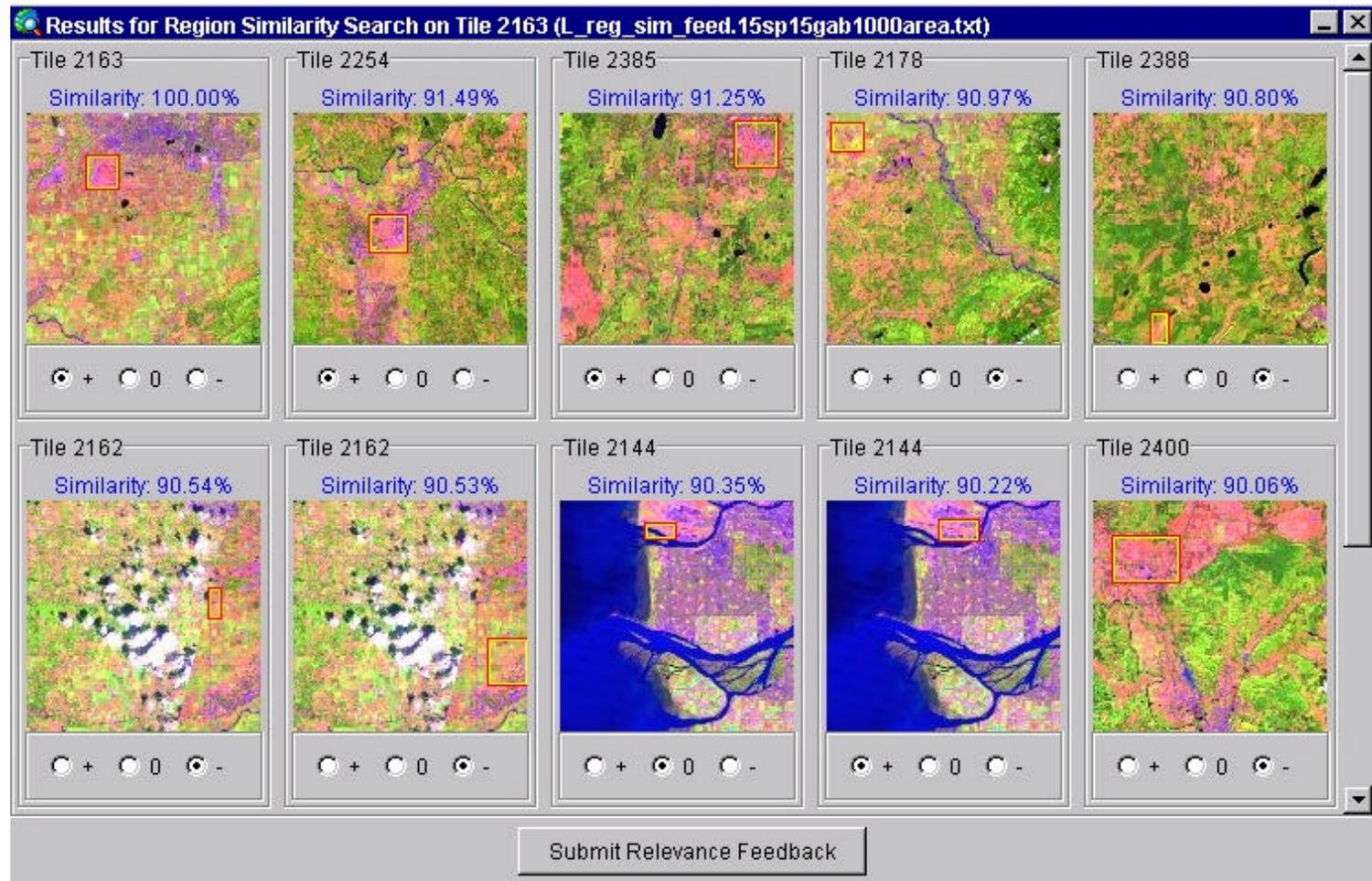
# Precision of data retrieval

- Experiments were performed for 15 regions (see summary on next slide).
- The best results are obtained using level 1 and 2 of HSEG and adding texture features improves the results of the majority of the queries.
- The results depend on the type of the query.
- We believe that using the relevance feedback for automated selection of the subsets of the features should improve the accuracy of search.

# Precision of data retrieval

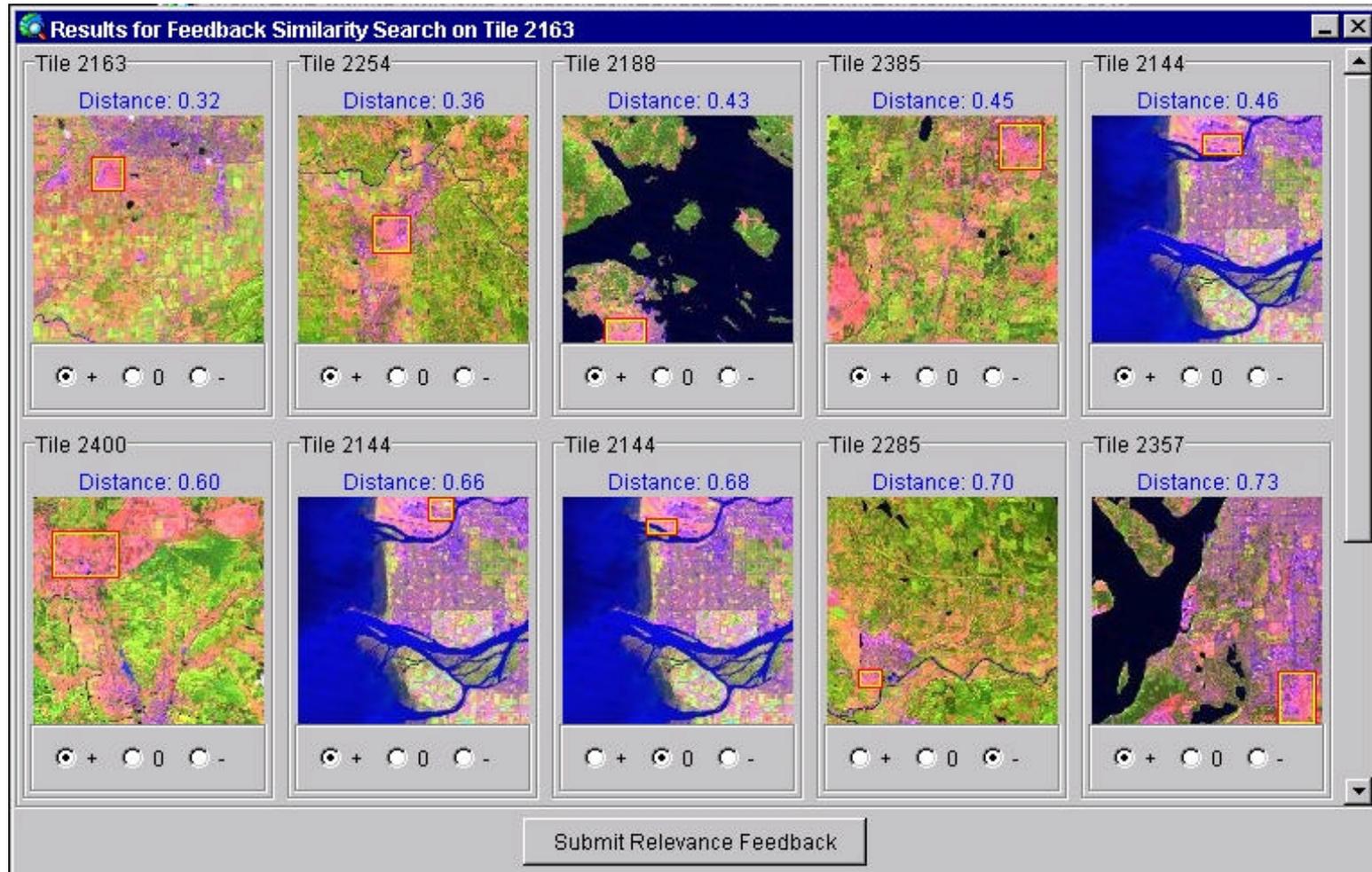
Feature	Average Precision
25 spectral CLARA clusters	0.7522999
25 spectral CLARA clusters with 10 Gabor texture clusters	0.7304257
HSEG level 1 region histograms	0.7746878
HSEG level 2 region histograms	0.7728281
HSEG level 2 clusters with 10 Gabor texture clusters	0.7649297
HSEG level 3 region histograms	0.7207362
HSEG level 3 clusters with 10 Gabor texture clusters	0.7528406
HSEG level 4 region histograms	0.7061142
HSEG level 6 region histograms	0.6435331
HSEG level 7 region histograms	0.4792615

# Relevance Feedback



Initial results search and relevance feedback for airport  
4 out of 10 images contain airports

# Relevance Feedback - cont.



Improved results after relevance feedback  
8 out of 10 images contain airports

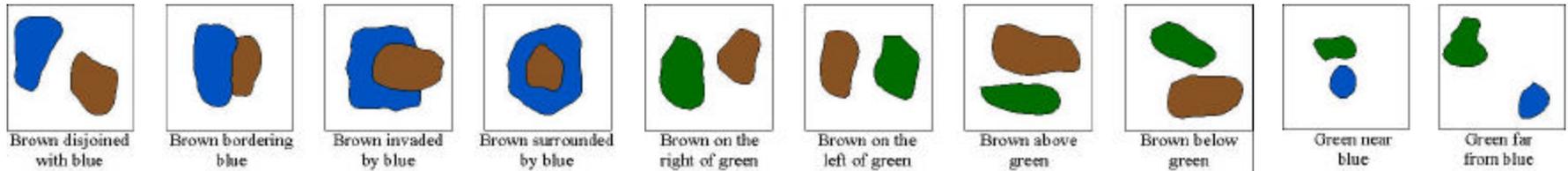
## Data Mining and Knowledge Discovery - cont.

- In addition to Region and Tile level similarity searches we also experimented with other data mining algorithms.
- The results were better when HSEG features were used.
- Extension of relevance feedback should automate mixing of features from different levels of HSEG output.

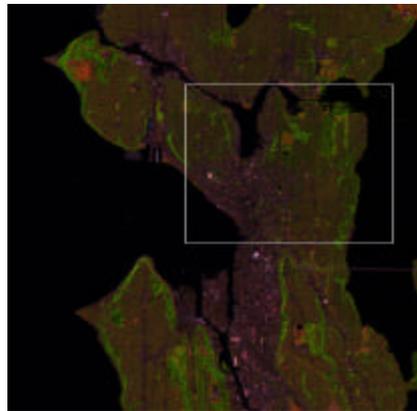
# Development of Visual Grammar

- Motivation:
  - Traditional pixel-level or region-level search algorithms cannot support complex query scenarios that contain many pixels and regions with different feature characteristics.
  - Two images with similar regions can have very different interpretations if the regions have different spatial arrangements.
  - Manual delineation by experts is not feasible for very large databases.

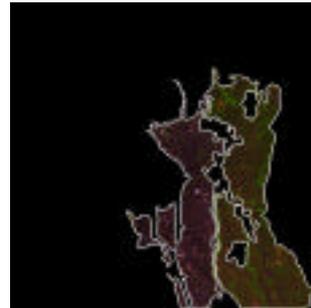
## Example spatial relationships:



## Example decomposition of a scene:



LANDSAT image of Seattle



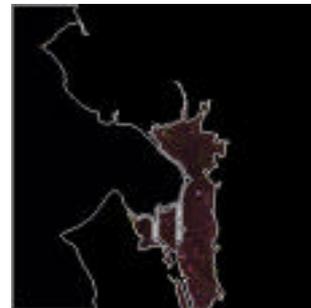
Residential area is bordering city



Residential area is bordering water



Park is surrounded by residential area



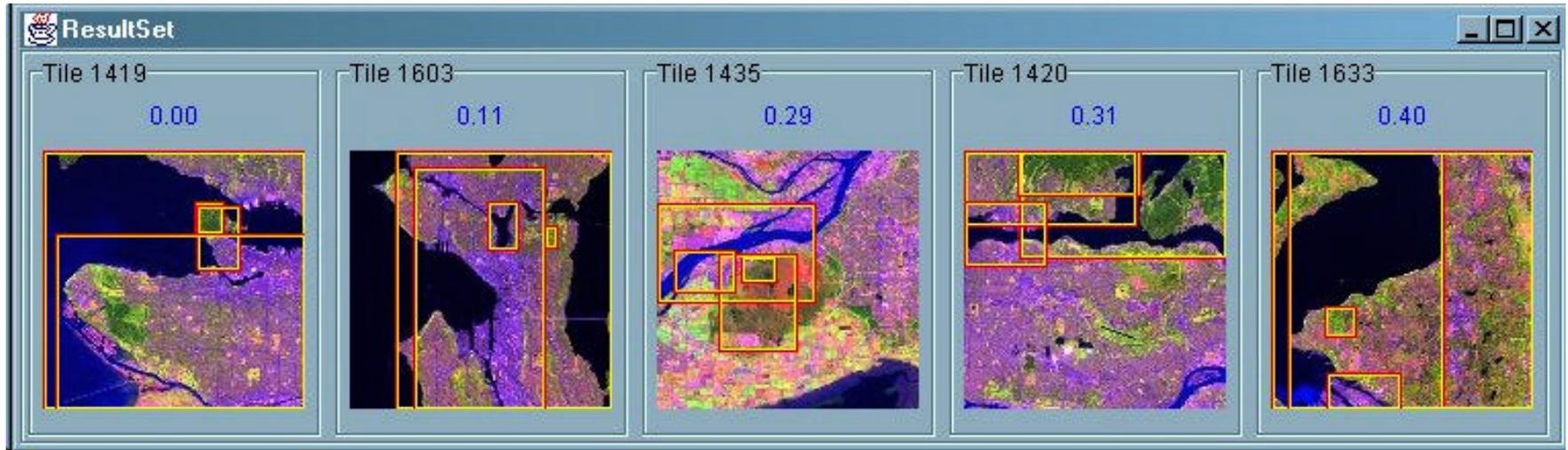
City is bordering water



Park is near water

- Decompose scene into regions: residential area, city, park and water.
- Compute spatial relationships of region pairs.
- Encode scene with the metadata, features and relationships of its regions.
- Searches and classification can be done to find other region groups that have both similar feature characteristics and similar spatial relationships.

Example of searches using the preliminary implementation.



Search for an image where residential area is bordering city and both are bordering water, and a park is surrounded by residential area and is also close to water.

Search for an image where forest is bordering water and is also to the north of a residential area.

# Advantages of Visual Grammar

- Combination of different data sources (e.g. hyper-spectral, texture, DEM).
- Construction of complex hierarchical scene models (e.g. an airport consists of buildings, runways and fields around them).
- Automatic generation of metadata for very large databases.
- Natural language search support: "Show me an image that contains a city surrounded by a forest that is close to a water source."

# Preliminary Study using ClassFuse and Clustering by Melting

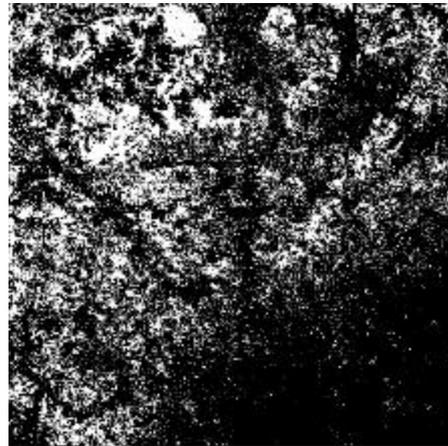
The study was performed using a X-SAR/SRTM SAR and DEM of Baltimore, MD. The results show the importance of the fusion of SAR image and DEM data and information for the purpose of scene understanding.

# SRTM Baltimore – Bayesian interactive classification – ClassFuse fusion of SAR image intensity, texture and DEM information

Intensity

DEM

Water



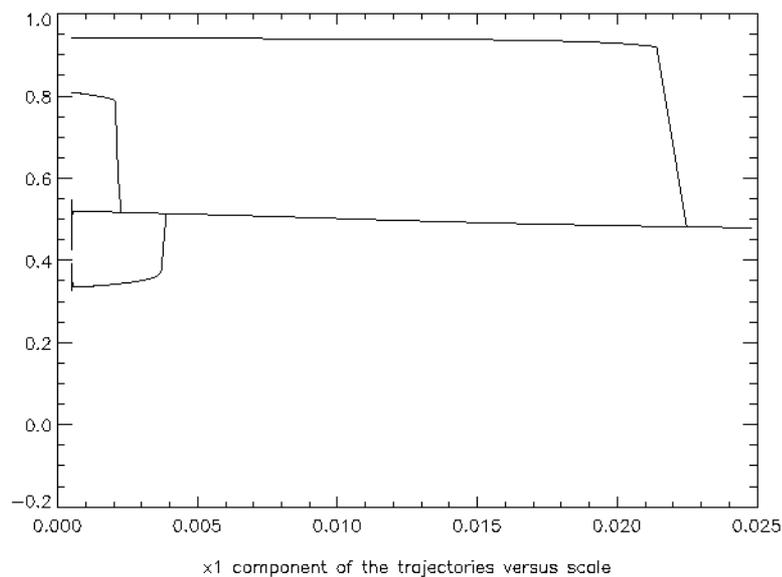
Urbanized

Bare Soil

Forest

# SRTM Baltimore – Clustering by melting – as image information mining tool

sequence of SRTM DEM classification and trajectory of clustres



# Technical Significance of Progress and Expected Impact on NASA

- The stage has been set for the exploitation of the image segmentation hierarchies produced by HSEG.
- Now that a robust, artifact-free parallel implementation is available for HSEG, full integration of HSEG into VisiMine will proceed quickly.
- Detailed study of the information bearing content of the segmentation hierarchy will also proceed.
- Expected impact on NASA will be significantly improved capability to explore NASA's vast image data archives.

# Linkable URL's for team members:

- Hierarchical Image Segmentation (J. C. Tilton at NASA's GSFC): <http://code935.gsfc.nasa.gov/code935/tilton>  
<http://www.nasamedicalimaging.com/hseg> .
- VisiMine (G. Marchisio at Insightful Corp.):  
<http://www.insightful.com> (click on "Products" and then click on "VisiMine") .
- Research by M. Datcu at DLR:  
<http://www.dfd.dlr.de/srtm/> and  
<http://www.vision.ee.ethz.ch/> (click on "Teaching" and then "Lectures").

# Facilities Used and Personnel Assigned to Projects

- Insightful Corp. (aka. MathSoft) occupies over 20,000 square feet of prime office space on the shore of Lake Union in downtown Seattle. Insightful has approximately 40 Unix workstations, 200 PCs, and 2 Macintosh computers in a networked environment. Five full-time systems administrators maintain the Insightful computer system.

# Facilities Used and Personnel Assigned to Projects - cont.

- NASA Goddard:

In addition to basic computing resources (Sun Workstations, PCs and associated peripherals), a new Beowulf PC cluster, called HIVE2, consisting of:

-> 64 dual-processor 1.2 GHz AMD Athlon nodes with a Myrinet interprocessor network connection (1 Gbps).

In addition, NASA is providing a number of test data sets.

# Facilities Used and Personnel Assigned to Projects - cont.

- Personnel at NASA Goddard:
  - J. C. Tilton, Ph.D. (NASA)
  - Ron Shiri, M.S. (Global Sciences and Technology)
- Insightful Corporation personnel:
  - G. Marchisio, Ph.D. (project Co-I)
  - K. Koperski, Ph.D., S. Aksoy, Ph.D., C. Tusk, M.Sc.
- Personnel at DLR:
  - M. Datcu, Ph. D. (project Co-I)
  - M. Ciucu and M. Quartulli (Ph. D. students at DLR)
  - S. Mansi and P. Pecciarini (M.S. students at DLR)

# References

- J. C. Tilton, G. Marchisio, K. Koperski, and M. Datcu “Image Information Mining Utilizing Hierarchical Segmentation” Proc. of IGARSS’02, Toronto, ON, June 2002 (to appear)
- K. Koperski, G. Marchisio, S. Aksoy, and C. Tusk “VisiMine: Interactive Mining in Image Databases” Proc. of IGARSS’02, Toronto, ON, June 2002 (to appear)
- K. Koperski, G. Marchisio, S. Aksoy, and C. Tusk “Applications of Terrain and Sensor Data Fusion in Image Mining” Proc. of IGARSS’02, Toronto, ON, June 2002 (to appear)
- S. Aksoy, G. Marchisio, K. Koperski, and C. Tusk “Probabilistic Retrieval with a Visual Grammar” Proc. of IGARSS’02, Toronto, ON, June 2002 (to appear)
- <http://dagm02.vision.ee.ethz.ch/workshops/index.en.html> and <http://isis.dlr.de/mining/> .