Classification of Raster Maps for Automatic Feature Extraction

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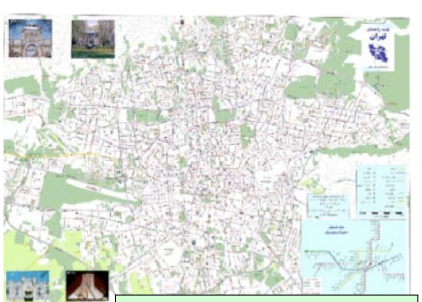
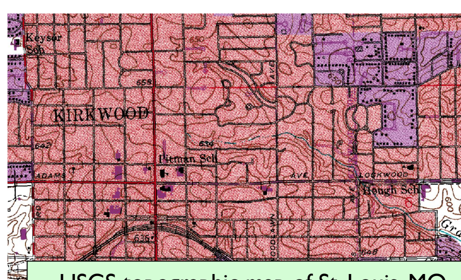
1

Motivation

- Raster map is a bitmap image of a map
- Raster maps are easily accessible
  - Contain information that is difficult to find elsewhere
  - Contain historical data



Travel map of Tehran, Iran

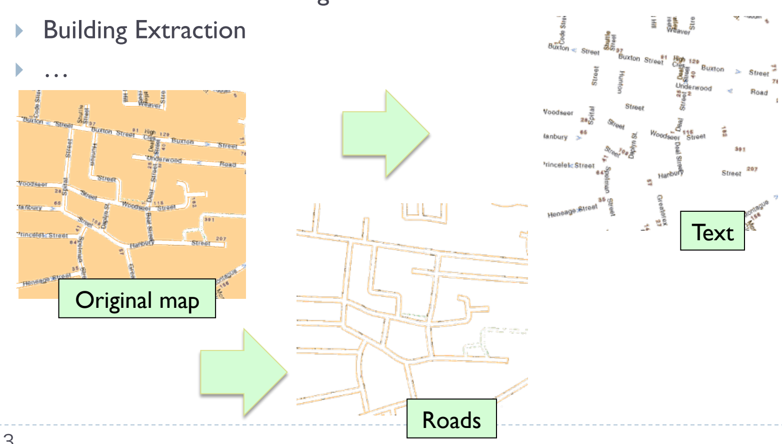


USGS topographic map of St. Louis, MO

2

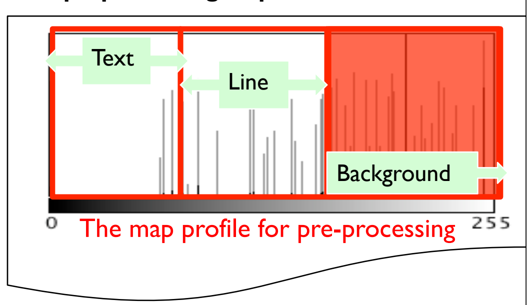
Exploit the geospatial information in raster maps

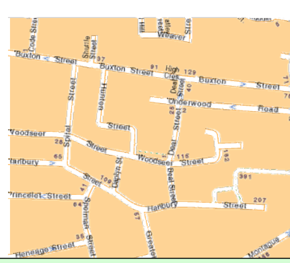
- Extracting geographic features from raster maps
  - Road Extraction
  - Text Extraction and Recognition
  - Building Extraction
  - …



Pre-Processing for feature extraction

- **Much of the feature extraction work relies on user input to extract the foreground pixels from the maps as a preprocessing step**
- **Pre-Processing examples:**
  - Convert to grayscale
  - Thresholding the grayscale histogram



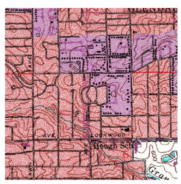


Convert road pixels to road vectors

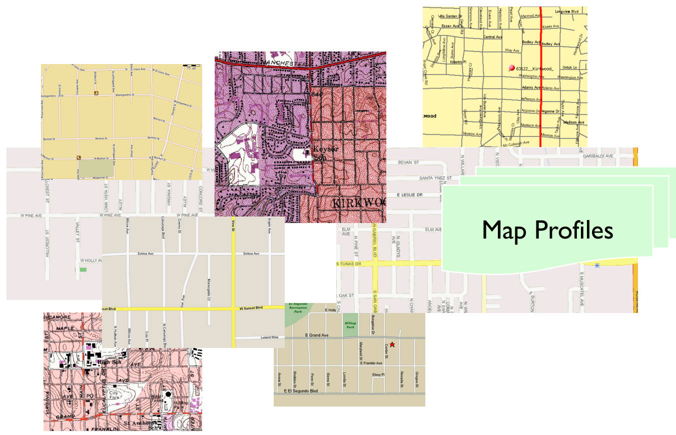
Convert text pixels to machine-editable text

Automatic determine an applicable map profile

- Can we automatically select a map profile for new input map?



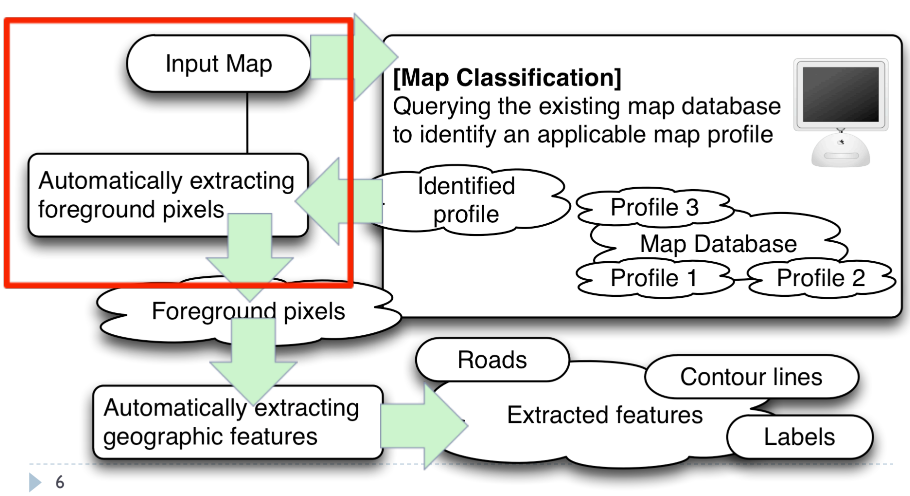
New map



Map repository

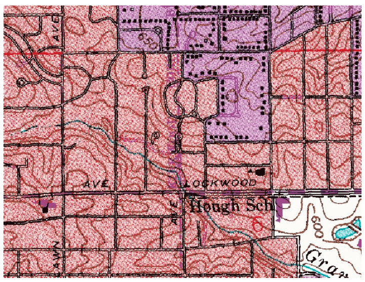
Automatic feature extraction with map classification

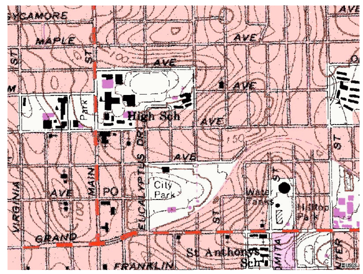
We can eliminate the manual pre-processing task using the map classification component



Can we use meta-data to determine a map profile?

- Meta-data such as map source, is not always available
- Maps from the same source can be very different
  - Two USGS topographic maps covering two different cities



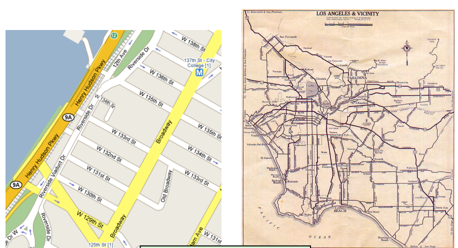


Content-based Image Retrieval (CBIR)

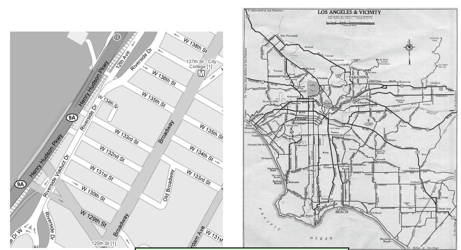
- CBIR is the technique to find images with similar ‘content’
  - Content similarity defined by the comparison features
- In our case, similar content means two raster maps shared the same map profile for extracting their foreground pixels
  - Comparison feature – Luminance-Boundary Histogram
  - Classifier – Nearest-Neighbor Classifier

Luminance or Color

- Luminance is chosen instead of using one or all of the Red, Green, and Blue components
  - One-dimensional features is more computational efficient
  - Luminance is the most representative component by design



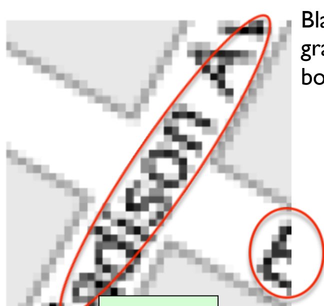
Color images



Grayscale images

Luminance-Boundary Histogram (LBH)

- LBH captures the spatial relationships between neighboring luminance levels in the map
- The two example maps have similar spatial relationship between their luminance levels



Map One

Blacks are surrounded by gray and white pixels in both maps

Map Two

High/Low Luminance-Boundary Histogram

- A set of LBH contain a High Luminance-Boundary Histogram (HLBH) and a Low Luminance-Boundary Histogram (LLBH)

How to generate the HLBH and LLBH?

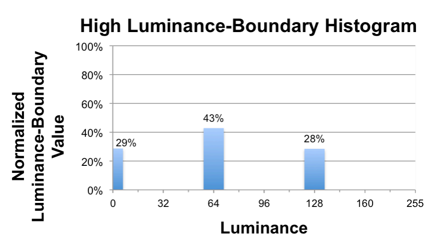
highlighted level

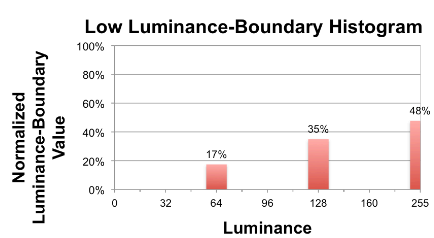
Nearest-Neighbor Classification

- Use L1 Distance to compare two sets of LBH

$$L_1 = \sum_{i=0}^{255} |HLBH1_i - HLBH2_i| + |LLBH1_i - LLBH2_i|$$

- A smaller distance indicates that the spatial relationships between luminance levels in one map are similar to the ones in the other map





Experiments

- Compare luminance-boundary histogram with
  - Color Histogram (CH):
    - Record the number of pixels of each color in a given color space
  - Color Moments (CM):
    - Based on statistical analysis of CH, i.e., average, standard deviation, and skewness
  - Color-Coherence Vectors (CCV):
    - Similar to CH, and further incorporates sizes of color regions into CH
- Two types of experiment:
  - Image retrieval queries
    - Evaluate the robustness of test features
  - Map classification tasks
    - Simulate a map classification component in a map feature extraction system

13

Test Data

- 60 test maps from 11 different sources
- Manually separated test maps into 12 class based on their luminance usage
- Insert the test maps to a map repository contained 1,495 raster maps

Map Source	Map Type	Map Counts	Intensity Interval
Google Maps	Digital	5	0–230
Live Maps	Digital	5	0–225
Yahoo Maps	Digital	5	0–200
MapQuest Maps	Digital	5	0–220
USGS topographic maps	Scanned	5	0–36
USGS topographic maps	Scanned	5	0–184
Rand McNally	Digital	5	0–190
Map24	Digital	5	0–215
TIGER/Line	Digital	5	0–110
OpenStreetMap	Digital	5	0–238
Streetmap.co.uk	Digital	5	0–175
ViaMichelin	Digital	5	0–234

Map Profiles

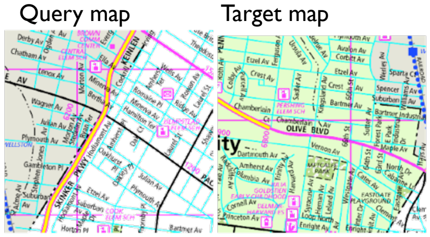
Experiments on Image Retrieval

- Test on Robustness
  - Remove a test class from the repository, such as a class of five test maps from Google Maps, namely G1, G2, G3, G4, and G5.
  - Insert one test map, say G1, into the repository (there is only one correct answer for each query in the repository)
  - Use G2 as the query image
  - Record the rank of G1 in the returned query results
  - Next, we used G3, G4, and G5 in turn as the query image
  - Remove G1 from the repository, insert G2, and repeat the experiments

Feature	Average Ranks	σ
LBH	5.95	24.15
Color-Coherence Vectors	15	52.14
Color Histogram	28.17	116.85
Color Moments	232.87	239.52

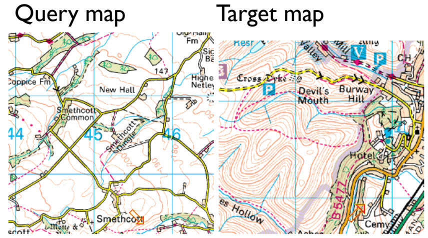
Image Retrieval Sample Results

Query map Target map



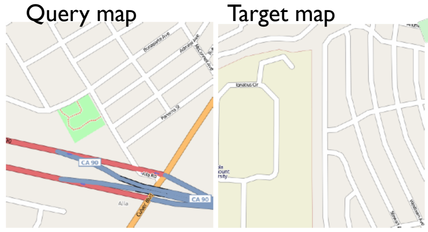
Rank: LBH/CCV/CH/CM 1/289/713/275

Query map Target map



1/15/269/724

Query map Target map



Rank: LBH/CCV/CH/CM 3/1/1/231

Non-shared luminance levels have strong luminance-boundary values
-> Lower the the comparative importance for the shared luminance levels

16

Experiments on Simulating Map Classification

- Simulate a real map classification task
- Example:
  - Remove one test map, such as G1, to query the repository (i.e., G1 represents a new input map and there are 4 correct answers)
  - If the first returned map was G2, G3, G4, or G5, then we had a correct classification
  - The accuracy is defined as the number of successful classifications divided by the total number of tested classifications

Feature	Accuracy
Luminance-Boundary Histogram	95%
Color-Coherence Vectors	86.67%
Color Histogram	88.33%
Color Moments	13.33%

17

Computation time on feature generation

- We implemented our experiments using Microsoft .Net running on a Microsoft Windows 2003 Server powered by a 3.2 GHz Intel Pentium 4 CPU with 4GB RAM
- Compare the top two features in the experiments
  - With 1,949 images
    - 428 seconds to generate the luminance-boundary histograms
    - 805 seconds to generate color-coherence vectors
    - The smallest test image in pixels is 130-by-350 and the largest image is 3000-by-2422

18

Related Work

- Map Classification using Meta-data (Gelernter, 09)
  - Answer queries such as finding the historical raster maps of a specific region for a specific year
- Image Comparison Features
  - **Shape**:
    - Histogram of oriented gradient - HoG (Dalal and Triggs, 05) for human detection
  - **Texture**:
    - Tamura texture features (Tamura et al., 78), Gabor wavelet transform features (Manjunath and Ma, 96)
    - Represent the overall texture of an image does not fit our goal
  - **Color**:
    - Color Histogram and Color Moments (Stricker and Orengo, 95) do not generate robust results
    - Color-Coherence Vectors (Pass et al., 96) requires threshold tuning

Discussion and Future Work

- Achieve 95% accuracy on map classification task
- Make it possible to extract geographic features (e.g., roads and text) automatically on new input maps
- LBH generation is efficient
- Future Work
  - Test with modern classifiers (e.g., SVM) or off-the-shelf content-based image retrieval (CBIR) systems
  - Integrate with our current system of map feature extraction