Spatial-Spectral Cross-Correlation for Change Detection -- A Case Study for Citrus Coverage Change Detection

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OUTLINE

- Background
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- Challenge & Solution
- Spatial-Spectral Cross Correlation
- Experiment & Results
- Conclusions

Background

- Why automatic citrus grove change detection
  - Critical to production inventory monitoring, map updating, and policy making
  - Various changes
    - Tree planted, removed, growing, degenerating
    - Citrus farm conversion and desertion
  - Huge work load
    - Over 700,000 acres in active production
    - Over 1200 maps & photographs analyzed and updated biennially
  - Current manual change detection
    - labor intensive, inefficient, non-ergonomic
  - Automation required

Background

- How to automate the citrus grove change detection
  - Open problem
  - Many change detection methods existing
    - Are they applicable?
    - Can they meet our requirements?
  - Developing a new method?

Challenge

- Florida citrus data conditions
  - Different sensors (digital/film)
    - Radiometric differences
    - Dynamic range differences (8-bit and 16-bit)
    - Resolution differences (1m and 2m) =>mixed-pixel
    - Spectral coverage differences (R/G/IR and R/G/B)
  - Unknown data acquiring conditions
    - Sun-angle
    - Atmospheric effects/weather condition
    - Season/date/time
  - Unknown sensor parameters and no calibration

Original Images

Figure 1. Original 2004 16-bit image

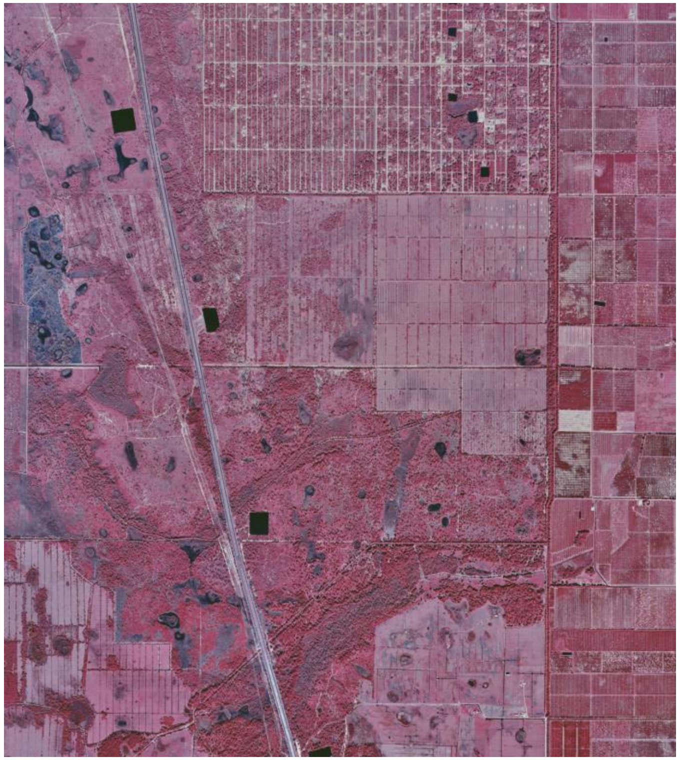
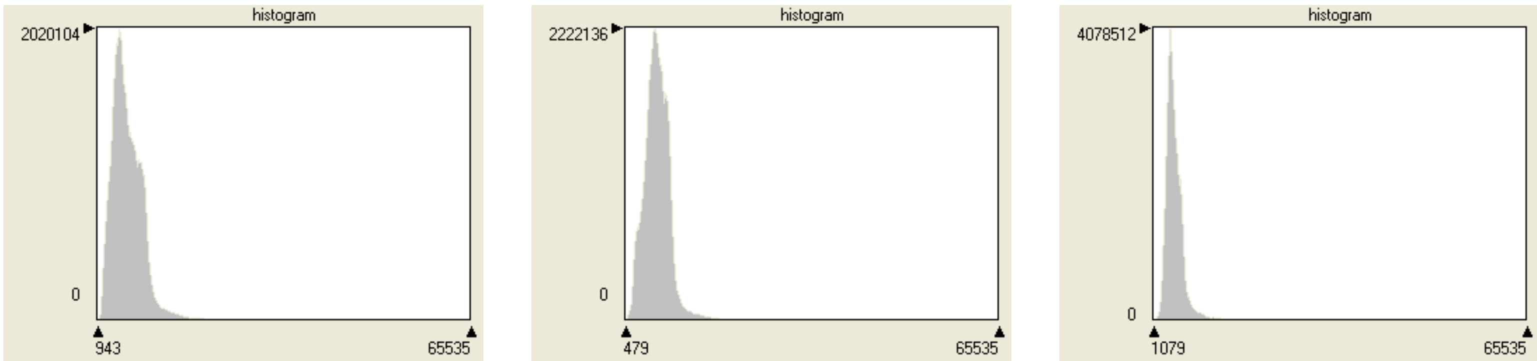


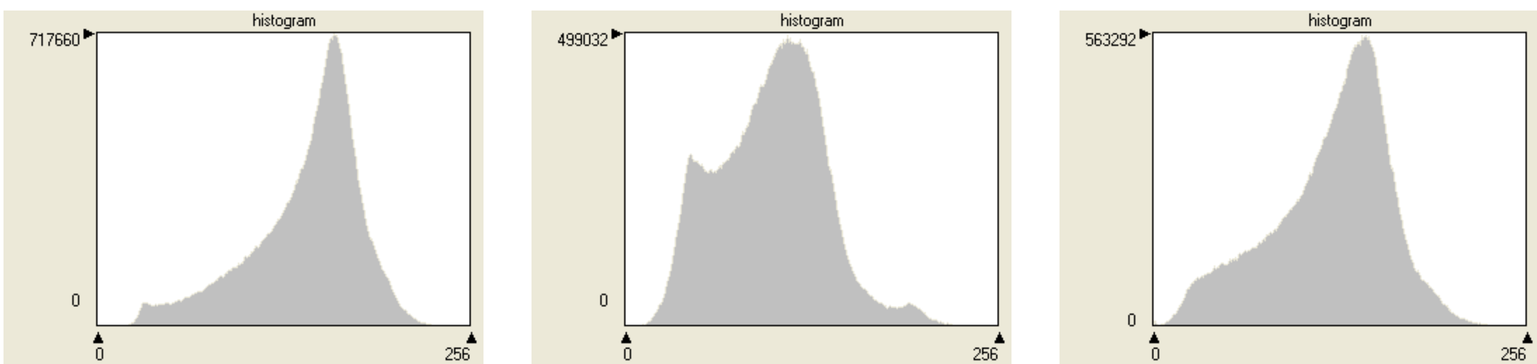
Figure 2. Original 1999 8-bit image

Histogram of Original Images



a) band-1 Histogram b) band-2 Histogram c) band-3 Histogram

Figure 3. Original 2004 16-bit image histograms



a) band-1 Histogram b) band-2 Histogram c) band-3 Histogram

Figure 4. Original 1999 8-bit image histograms

Change Detection Methods (I)

- Pre-classification
  - Various methods:
    - Image differencing (normalized/non-normalized)
    - Change vector analysis
    - Inner product analysis
    - Image ratioing
    - Vegetation index differencing
    - Spectral cross-correlation
    - Principal component analysis (PCA)
  - All are spectral based
  - All are sensitive to misregistration, mixed pixel
  - All are straightforward and easy to implement except PCA
  - Some are sensitive to radiometric distortion (difference)
  - Some are sensitive to dynamic range

Change Detection Methods

- Post-classification
  - Two steps:
    - Classification
    - Interpreting and Comparing classification results
  - Detection accuracy depends on the classification accuracy
    - Upper bound : Difference of two image classification errors
    - Lower bound : Sum of two classification errors
  - Complicated
    - Experienced & well trained analyst needed
  - Interpretation of classification result needed
    - Extra errors may be introduced
  - Intra-class change is not defined
    - Difficult in detecting citrus growth
  - Suitable for large scale land coverage change detection (many cover types involved)

What We Expected

- Minimum human-machine interaction
  - Minimum experience and training for operation
  - Minimum preprocessing
- Easy to understand and easy to implement
- Robust to different image data conditions
  - Robust to radiometric difference
  - Invariant to dynamic range
  - Robust to the mixed-pixels
  - Robust to the noise

Solution

- Utilize the spectral correlation
    - Invariant to image dynamic range
    - Robust to Radiometric difference
    - Easy to understand and easy to implement
    - Minimal pre-processing
    - But sensitive to mixed-pixel and to noise
- How to improve it
  - Develop a novel method by using the spatial information
  - How to use the spatial information
    - Integrate the spatial correlation concept
- Result -Spatial-Spectral Cross Correlation

Spectral Cross Correlation

Let f(x, y,k) and g(x, y,k) be two multi-spectral images
Then the spectral cross correlation coefficient is given by:

$$c(i,j) = \frac{[g(i,j) - \bar{g}(i,j)]^T [f(i,j) - \bar{f}(i,j)]}{\sqrt{\left\| g(i,j) - \bar{g}(i,j) \right\|^2} \sqrt{\left\| f(i,j) - \bar{f}(i,j) \right\|^2}}$$

Where

$$g(i,j) = \begin{bmatrix} g(i,j,1) \\ g(i,j,2) \\ \dots \\ g(i,j,L) \end{bmatrix} \qquad f(i,j) = \begin{bmatrix} f(i,j,1) \\ f(i,j,2) \\ \dots \\ f(i,j,L) \end{bmatrix}$$

- No spatial information, Spectral signature similarity only
- Sensitive to mixed-pixels and noise.

Spatial Cross Correlation

Let f(x, y) and g(x, y) be two single band images

Then the spectral cross correlation coefficient is given by:

$$c(i,j) = \frac{\sum_{x\in W}\sum_{y\in W}[g(i+x,j+y)-\bar{g}(i,j)][f(i+x,j+y)-\bar{f}(i,j)]}{\sqrt{\sum_{x\in W}\sum_{y\in W}[g(i+x,j+y)-\bar{g}(i,j)]^2}\sqrt{\sum_{x\in W}\sum_{y\in W}[f(i+x,j+y)-\bar{f}(i,j)]^2}}$$

Where

$$\bar{g}(i,j) = \frac{1}{W^2}\sum_{x\in W}\sum_{y\in W} g(i+x,j+y), \quad \bar{f}(i,j) = \frac{1}{W^2}\sum_{x\in W}\sum_{y\in W} f(i+x,j+y)$$

- Single band, no spectral signature, spatial similarity only
- Not proper for change detection

Normalized Spatial-Spectral Cross Correlation (SSC)

Let f(x, y,k) and g(x, y,k) be two multi-spectral images

Then the spectral cross correlation coefficient is given by:

$$c(i,j) = \frac{\sum_{x\in W}\sum_{y\in W}[g(i+x,j+y)-\bar{g}(i,j)]^T[f(i+x,j+y)-\bar{f}(i,j)]}{\sqrt{\sum_{x\in W}\sum_{y\in W}\left\|g(i+x,j+y)-\bar{g}(i,j)\right\|^2}\sqrt{\sum_{x\in W}\sum_{y\in W}\left\|f(i+x,j+y)-\bar{f}(i,j)\right\|^2}}$$

Where

$$\bar{g}(i,j) = \frac{1}{W^2L}\sum_{x\in W}\sum_{y\in W}\sum_{k=1}^{L} g(i+x,j+y,k),\quad \bar{f}(i,j) = \frac{1}{W^2L}\sum_{x\in W}\sum_{y\in W}\sum_{k=1}^{L} f(i+x,j+y,k)$$

- Multi-spectral signature and local spatial similarity

Experiments & Results

- Implementation & preprocessing
  - 2 meter 1999 Image re-sampled into 1 m
  - Images were pre-registered individually
  - Correlation computed over overlapping area
  - Change maps thresholded by ISODATA algorithm
- Results
  - Comparing correlation maps of SC and SSC
  - Comparing change maps between SC and SSC
  - Zooming the correlation maps

Enhanced Original Images

Figure 5. Enhanced 2004 16-bit image

Figure 6. Enhanced 1999 8-bit image

Correlation Maps

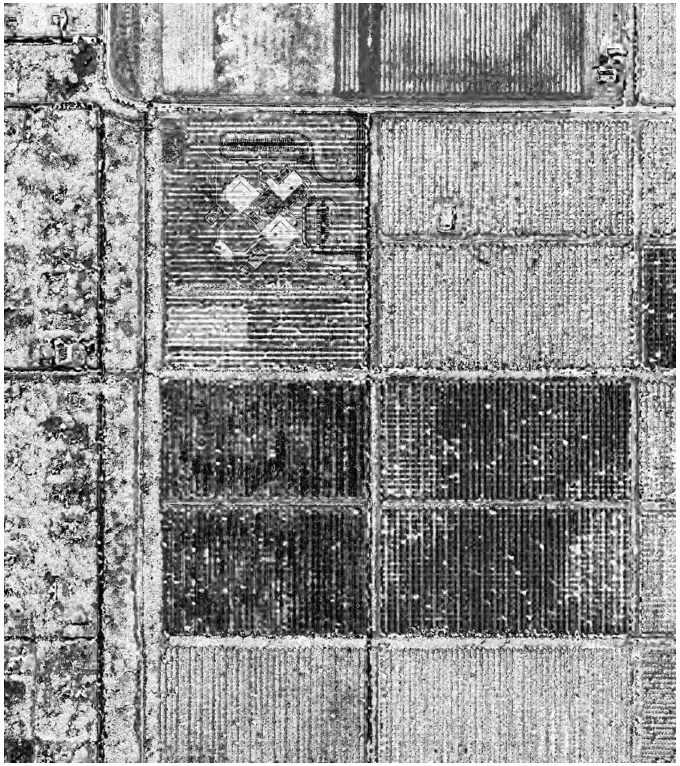


Figure 7. Spectral Correlation Map (SC)
W=1

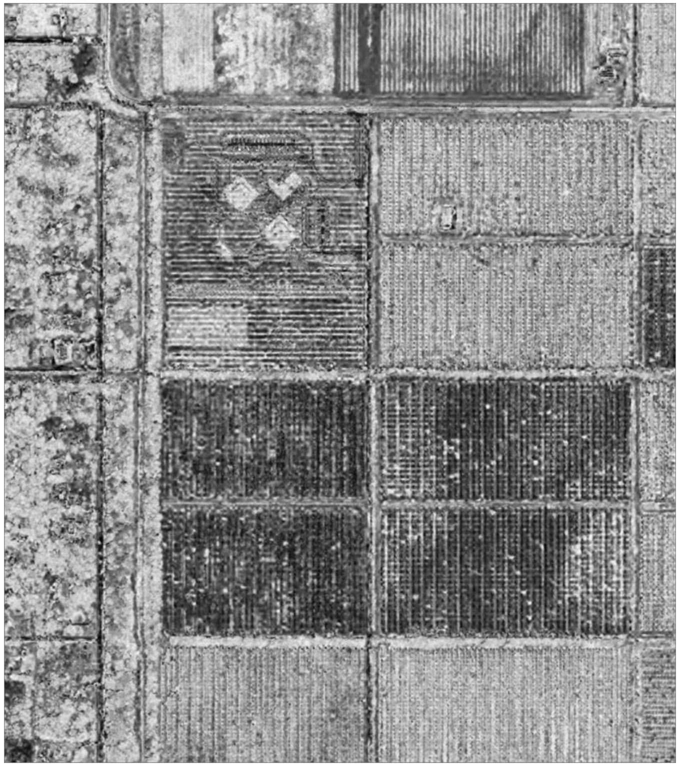
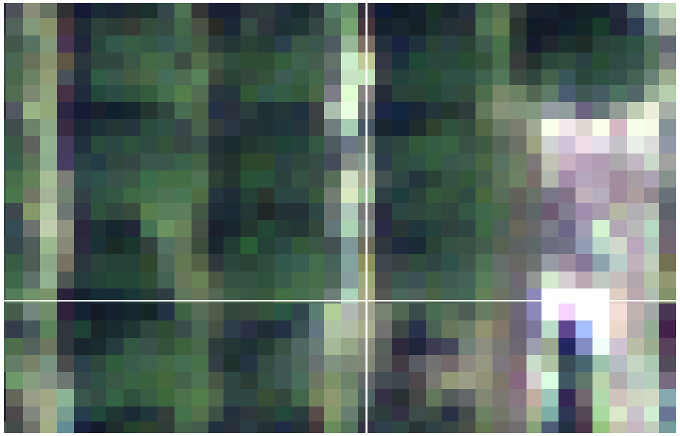
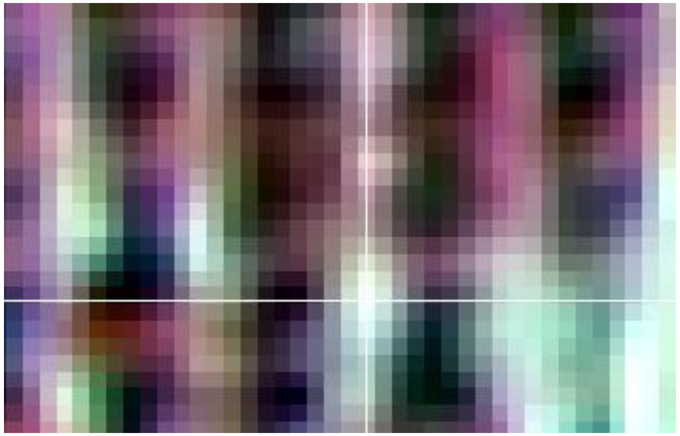


Figure 8. Spatial-Spectral Correlation Map
W=3

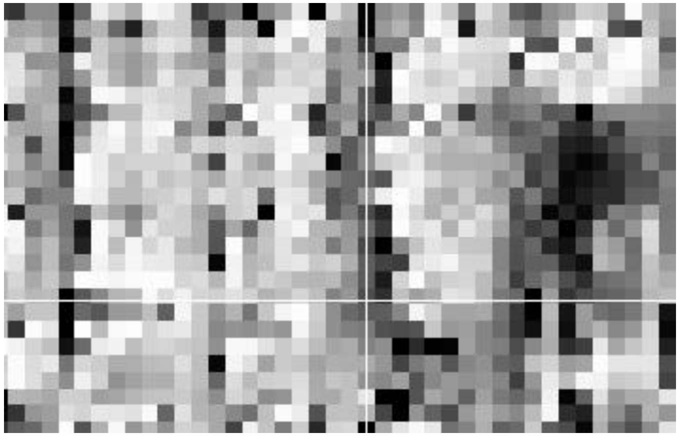
Zoomed Correlation Maps



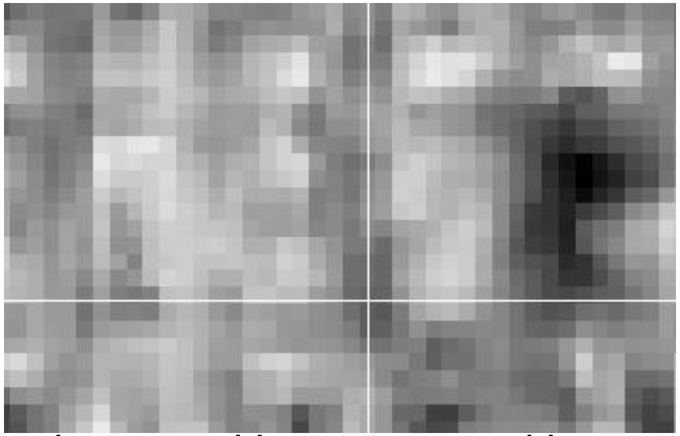
a. Enhanced 2004 16-bit image



b. Enhanced 1999 8-bit image



c. Zoomed in SC Map



d. Zoomed in SSC Map with W=3

Figure 11. Pixel view

Change Maps

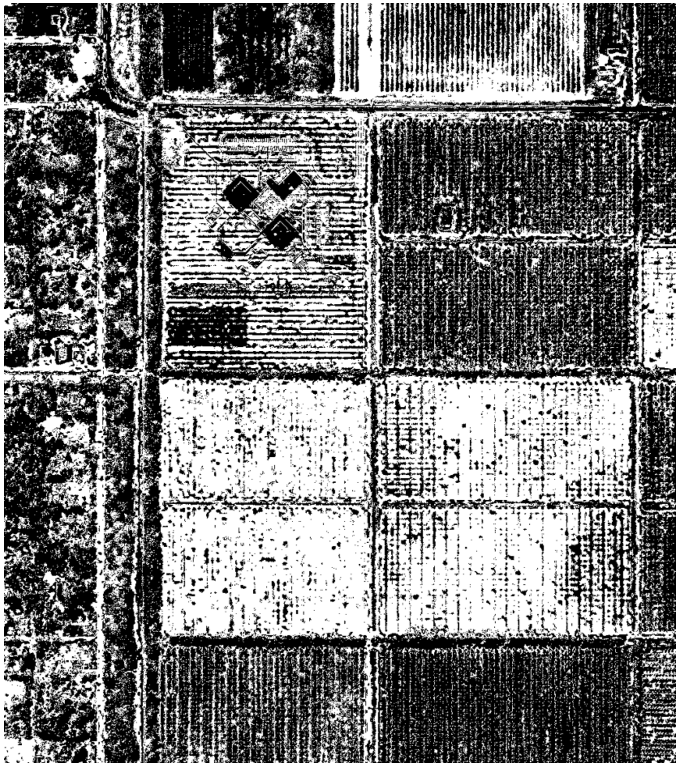


Figure 9. Threshold Change Map from SC Map W =1

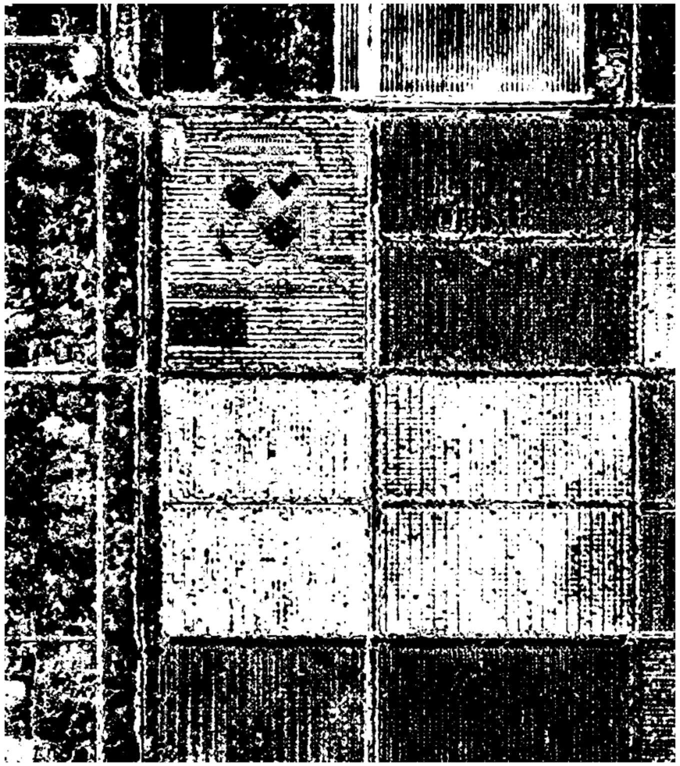


Figure 10. Threshold Change Map from SSC Map with W =3

Conclusions

- Presented a new concept of spatial-spectral cross correlation
  - Generalized the spatial correlation and the spectral correlation method into a spatial-spectral domain;
  - Proved both spatial correlation and spectral correlation are special cases of the Spatial-Spectral correlation.
- Spatial-spectral cross correlation method
  - Spatial and spectral information
  - Minimal pre-processing (only re-sampling)
  - Robust to radiometric differences
  - Invariant to image dynamical range differences
  - Robust to noise as evidenced by less salt & pepper effect
  - Robust to the mixed-pixel effect
  - Less sensitive to misregistration.

Conclusions

  - More attractive for multi-temporal image change detection with different spatial resolutions because of the robustness to the mixed-pixel effect
- Shortcomings:
  - Relatively computational intensive
  - Not suitable for saturated image (with the small variance)
- Overall, this method can be used for generating a correlation map as a global navigation tool or as a local change indication for images of different spatial resolutions

Thank You!

Question?