# Unbiased Histogram Matching Quality Measure For Optimal Radiometric Normalization

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#### OUTLINE

- Why Histogram Matching for Radiometric Normalization
- Histogram Matching Method
- Histogram Matching Optimization for Radiometric Normalization
- Performance Metric Similarity Measurement
- Experiments & Results
- Conclusions

### Why Histogram Matching for Radiometric Normalization

- Radiometric correction is critical to change detection and other applications
- Why histogram matching normalization?
  - It's a relative radiometric normalization method;
    - Less expensive, always feasible,
    - applicable across sensors.
    - No sensor information required;
  - No need to subjectively select pseudo invariant areas for parameter estimation
  - Most imageries involves only small portions of changes
  - The nonlinear transformation fits better for nonlinearity

### Histogram Matching Method

Let  $p_u(x_i)$  and  $p_v(y_i)$  be histograms of grey level  $u=x_i$  and  $v=y_i$ . Their distributions are:

$$w_u(n) = \sum_{i=0}^{n} p_u(x_i)$$
,  $w_v(k) = \sum_{i=0}^{k} p_v(y_i)$ ,  $n, k = \{0, ..., L-1\}$ 

Then, the histogram matching of the given  $u=x_i$ , is given by  $v=y_k$ , where k is the minimum value which satisfies  $w_u(n) <= w_v(k)$ .

# Histogram Matching Optimization for Radiometric Normalization

- Why histogram matching optimization?
  - Different reference image yields different residual error;
  - For change detection, either images can be selected reference;
  - Which one is of better performance?
- How to determine which one is better?
  - Define a similarity measure:

$$s_{rk}(x, y, k) = f(I_r(x, y, k), I_{rh}(x, y, k))$$

Find reference image with best similarity for histogram matching:

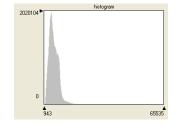
$$MAX\{s_{rk}(x, y, k)\}, \forall k \in \{1, 2, ..., K\}, r\{1, 2, ..., L\}$$

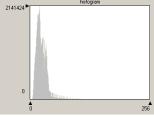
Specifically, which similarity measure is proper?

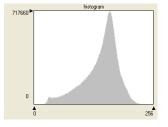
#### Performance Metric - Similarity Measures

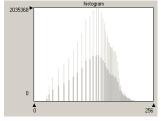
- There are many similarity measures existing;
  - Euclidean distance used of normalization performance comparison;
  - Manhattan distance used for performance measurement of histogram matching;
  - Both are isotropic and biased for variables with different scale.

#### Example:









В

A scale invariant measure needed!

#### Image Ratioing

The scale invariant similarity measure - Image ratio:

$$r(i, j, k) = \frac{I_r(i, j, k)}{I_{rh}(i, j, k)},$$
 for  $k \{1, 2, ..., K\}$ 

- It is simple, but don't reflects absolute radiance change;
- It is asymmetry metric
  - The ratio differs dramatically when switching the numerator and denominator;
  - Hard to perform thresholding;
- It is not summable. e.g.  $(r_1+r_2)/2 = (0.8+1.2)/2=1 => No Change$
- It's not suitable for images from different spectral bands

#### Symmetric Image Ratio (SIR)

To overcome these shortcomings, a new symmetric image ratio is proposed as following:

$$r_{rk}(i, j) = \begin{cases} \frac{I_r(i, j, k)}{I_{rh}(i, j, k)}, \forall I_r(i, j, k) \leq I_{rh}(i, j, k) \\ \frac{I_{rh}(i, j, k)}{I_r(i, j, k)}, \forall I_r(i, j, k) > I_{rh}(i, j, k) \\ 0, \forall (I_r(i, j, k) = 0 \lor I_{rh}(i, j, k) = 0) \end{cases}$$

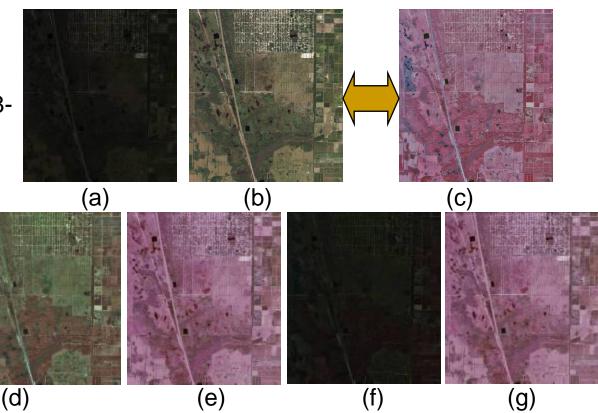
Summable - Overall similarity of two images is given by:

$$s_{rk} = \sum_{i=1}^{M} \sum_{j=1}^{N} r_{rk}(i, j), k \{1, 2, ..., K\}, r \{1, 2, ..., L\}$$

#### Experiments & Results

#### Original & Histogram Matched Images

Original images (a) unclipped 2004 8-bit image; (b) Clipped 2004 8bit image; (c) 1999 8-bit image;



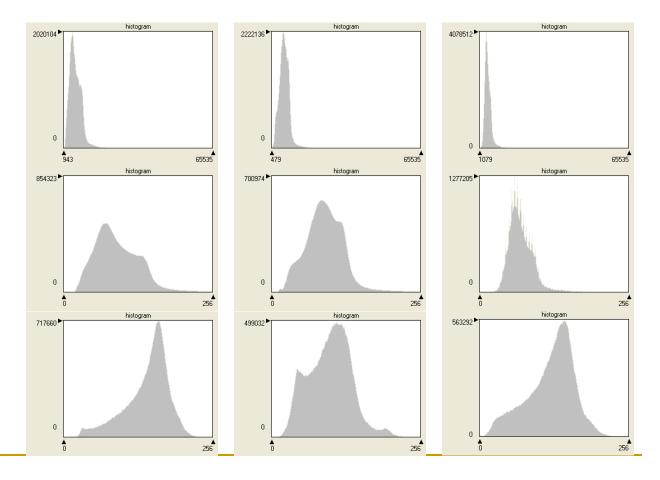
Histogram matched images: (d)1999 image with clipped 2004 reference; (e) Original 2004 image with 1999 reference; (f)1999 image with unclipped 2004 reference; (g) Unclipped 2004 with 1999 reference

#### Reference Image Histograms

Unclipped 2004 8bit image histograms

Clipped 2004 8-bit image histograms

Original 1999 8-bit image histograms



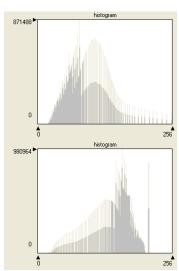
#### Histogram Matched Image Histograms

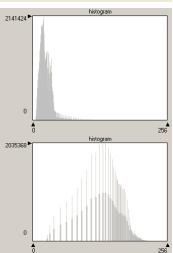
Histogram matched original 1999 image histograms with clipped 2004 image as reference

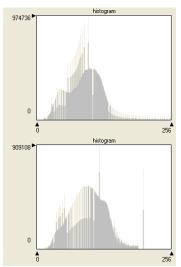
Histogram matched 2004 clipped image histograms with 1999 image as reference

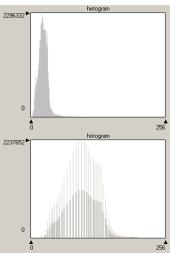
Histogram matched 1999 image histograms with unclipped 2004 image as reference

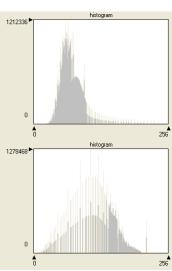
Histogram matched unclipped 2004 image histograms with original 1999 image as reference

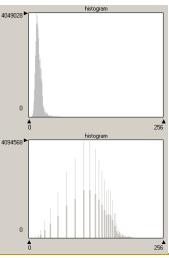












#### Manhattan Distance Measure Results

 The Manhattan distance measurement of image similarity of the nonnormalized images and the histogram matching normalized images with different reference images and different bands.

Table 1. Manhattan distance measuring results for images without image clipping.

Unclipped 2004 image	Band 1	Band 2	Band 3
No Normalization	5,165,526,637	3,334,340,163	4,489,143,486
HMN, 1999 Image as Reference	1,333,636,088	1,164,335,668	1,238,088,703
HMN, 2004 Image as Reference	440,286,597	318,965,703	223,107,908

Table. 2. Manhattan distance measuring results for images with image clipping.

High-bit clipped 2004 image	Band 1	Band 2	Band 3
No Normalization	2,460,670,698	1,242,35,0692	2,344,830,977
HMN, 1999 Image as Reference	1,353,792,013	1,180,279,785	1,255,995,069
HMN, 2004 Image as Reference	1,584,393,561	1,159,968,546	825,605,177

#### Symmetric Image Ratio Measure Results

Table 3. Symmetric image ratio measuring results for images without image clipping.

Unclipped 2004 image	Band 1	Band 2	Band 3
No Normalization	7,804,863	11,139,156	7,493,628
HMN, 1999 Image as Reference	35,314,399	33,674,501	34,378,529
HMN, 2004 Image as Reference	30,706,733	33,069,553	35,408,049

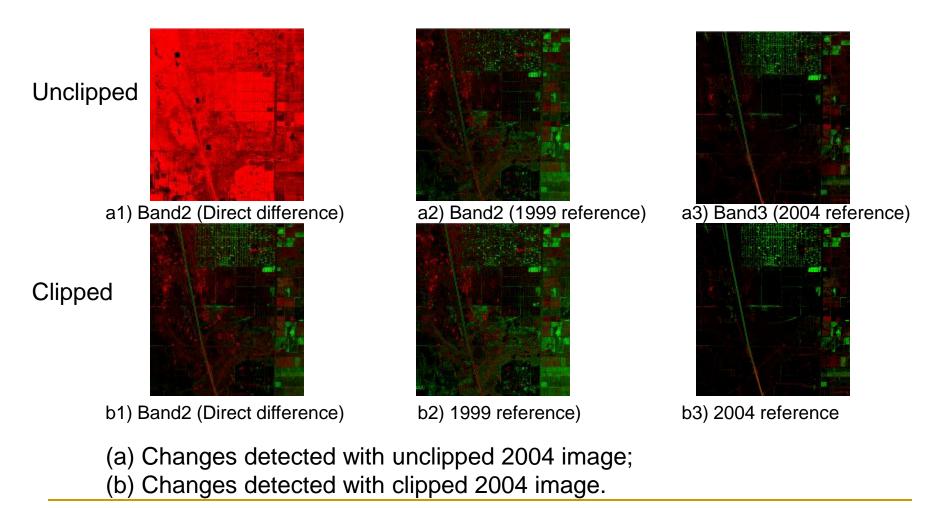
Table 4. Symmetric image ratio measuring results for images with image clipping.

High-bit clipped 2004 image	Band 1	Band 2	Band 3
No Normalization	27,544,433	33,053,400	25,968,637
HMN, 1999 Image as Reference	35,325,968	33,686,762	34,374,198
HMN, 2004 Image as Reference	31,100,131	33,389,944	35,622,059

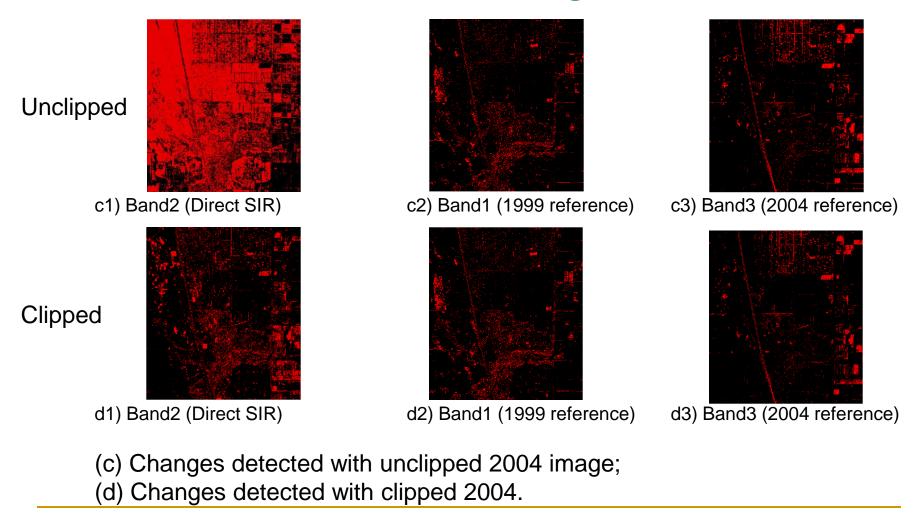
#### Observations

- From Table 1 & 2 (for Manhattan), the reference and bands with minimum differences are unchanged;
- After clipping (compact histogram spread), the difference significantly changed;
- The ordinal rank of the similarity changes after clipping;
- From Table 3&4 (for SIR), the reference and bands with minimum differences are unchanged;
- After clipping, the difference significantly changed if no HM, but no change after HM;
- The ordinal rank of the similarity unchanged;
- SIR results for corresponding reference & band remain roughly same regardless if the image clipped or not; This means not bias!
- However, the ordinal rank of the similarity from SIR differs from that from Manhattan distance measure; Especially, Band 1 using 1999 ref, it has highest similarity in SIR, but not in Manhattan.

### Change Maps from Manhattan Distance with Different Reference Images



## Change Maps from Symmetric image Ratio with Different Reference Images



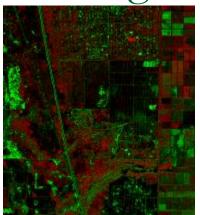
#### Conclusions

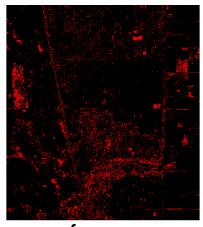
- The new symmetric image ratio is scale invariant and unbiased to the low bit concentrated image histogram
  - SIR results show that the clipping does not affect result;
- It is symmetric and is consistently ranging in [0, 1]
  - 0 represents least similarity
  - 1 represents the maximum similarity;
- It is better than regular Image ratioing for change detection
  - Consistent measure, normalized values, and easy thresholding;
- Quality control needed for picking band for data from multi-sensors
  - Make sure the interested objects not suppressed.
- But it inherits some regular image ratioing drawbacks:
  - Does not reflect physical radiometric
  - Enhances some land cover spectral features while suppressing others;

### Comparison of Manhattan Distance and

Symmetric Image Ratio for Band 1

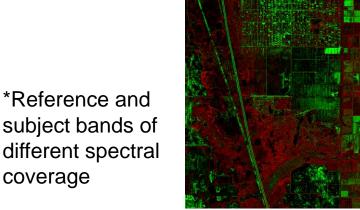
Manhattan

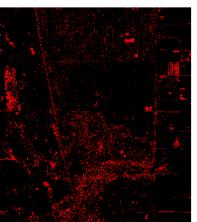




SIR

Change map with 1999 image as reference





Change map with 2004 image as reference

#### THANK YOU!

#### **QUESTIONS?**

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