MRF and Dempster-Shafer Theory for simultaneous shadow/vegetation detection on high resolution aerial color images

PhD research

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Outline

1. Introduction
2. DS evidence theory for shadow/vegetation detection
   - Motivation
   - Theory of Belief functions
   - Application to shadow/vegetation detection
3. Contextual Information
   - Markov random field
   - DS theory in Markovian context
4. Results

Process line

Shadow/vegetation detection ⟶ Building detection ⟶ Building classification ⟶ Change detection (updating building database)

At time n

At time n+1

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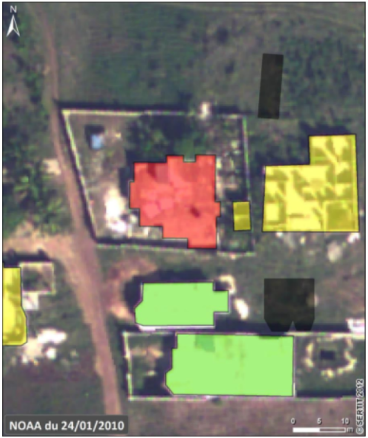
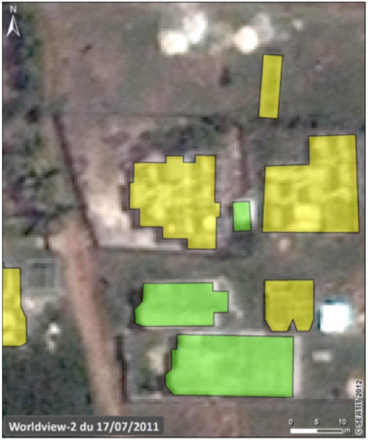


At time n



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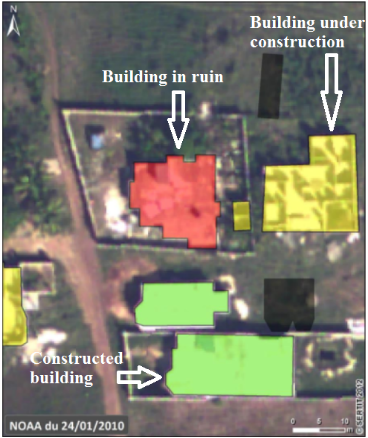

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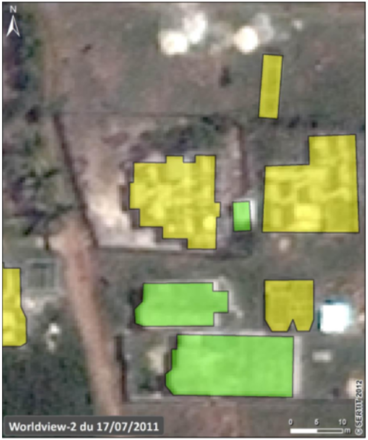

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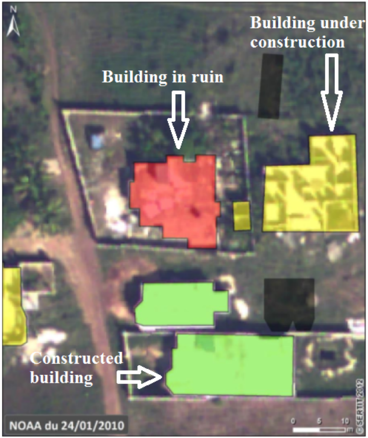

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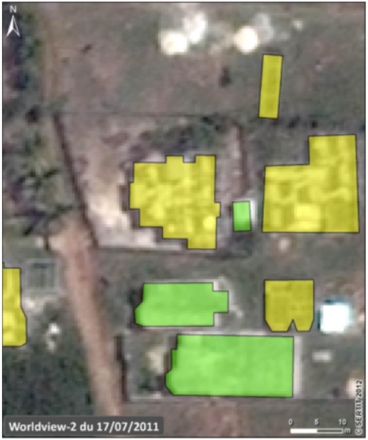

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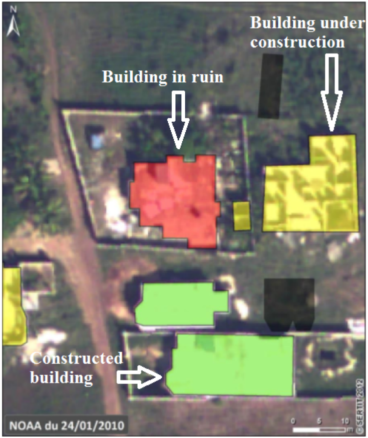
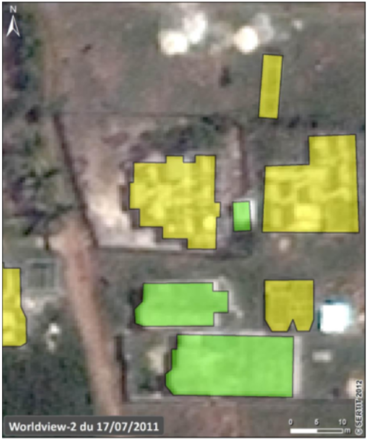


At time n



At time n+1

Motivation

- Drawbacks of sequential shadow/vegetation detection: vegetated pixels covered by shadow are wrongly classified.
- Represent and handle imprecise and uncertain information.
- Combine different sources of information.

Dempster-Shafer Belief Functions

- Frame of discernment: $\Theta = \{H_i\}, 1 \leq i \leq N$.
- A mass function on Θ is a function $m : 2^\Theta \longrightarrow [0, 1]$ such that the following two conditions hold:

$$m(\emptyset) = 0$$
$$\sum_{A \subseteq \Theta} m(A) = 1$$

- $m(A)$ measures the degree of belief in the exact proposition.

Dempster-Shafer Belief Functions

- Belief (Bel) function:

$$Bel(A) = \sum_{B \subseteq A} m(B)$$

measures the minimum uncertainty value about hypothesis A.

- Plausibility (Pls) function:

$$Pls(A) = \sum_{B \cap A \neq \emptyset} m(B)$$

measures the maximum uncertainty value about hypothesis A.

- The length of belief interval $[Bel(A), Pls(A)]$: imprecision about the uncertainty value.

Combining the evidences

Suppose m_1 and m_2 are two mass distributions from two sources S_1, S_2, defined over Θ. Then $m_1 \oplus m_2$ is given by:

Orthogonal sum

$$m_1 \oplus m_2(A) = \begin{cases} 0 & \text{if } A = \emptyset \\ \dfrac{1}{1-K} \displaystyle\sum_{B \bigcap C = A \neq \emptyset} m_1(B).m_2(C) & \text{if } \emptyset \neq A \subseteq \Theta \end{cases}$$

$K = \displaystyle\sum_{B \bigcap C = \emptyset} m_1(B).m_2(C)$: normalization constant.

Application to shadow/vegetation detection

Image segmentation with 3 classes:

- ω_1 : shadow
- ω_2 : vegetation
- ω_3 : other

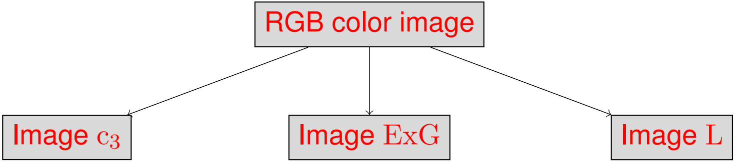
Application to shadow/vegetation detection

Image segmentation with 3 classes:

- ω_1 : shadow
- ω_2 : vegetation
- ω_3 : other

Frame of discernment: $\Theta = \{H_1, H_2, H_3\}, \quad H_i = \{\omega_i\}$

Application to shadow/vegetation detection

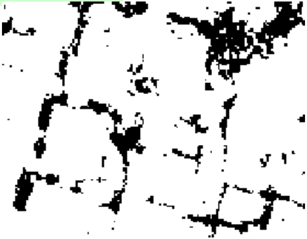


Application to shadow/vegetation detection

RGB color image

Image c_3 | Image ExG | Image L

$$c_3 = \arctan\left(\frac{B}{\max(R, G)}\right)$$

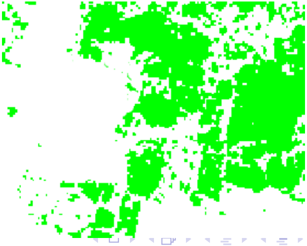


Application to shadow/vegetation detection

RGB color image

Image c_3 | Image ExG | Image L

$$\mathrm{ExG} = \frac{2 \times \mathrm{G} - \mathrm{R} - \mathrm{B}}{\mathrm{R} + \mathrm{G} + \mathrm{B}}$$



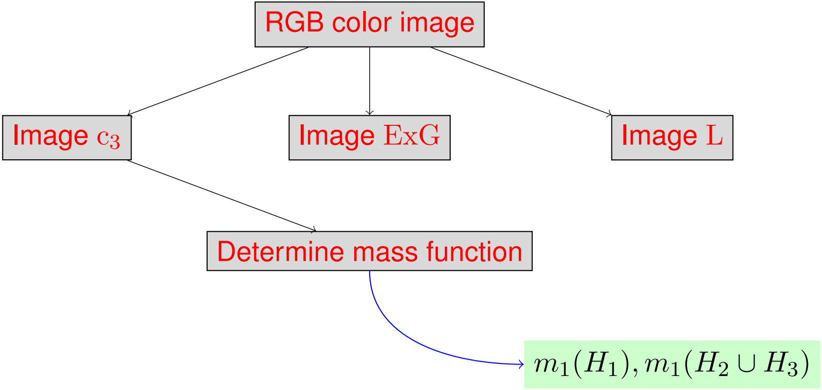
Application to shadow/vegetation detection

RGB color image

Image c_3 | Image ExG | Image L

$$L = \frac{R + G + B}{3}$$

Application to shadow/vegetation detection



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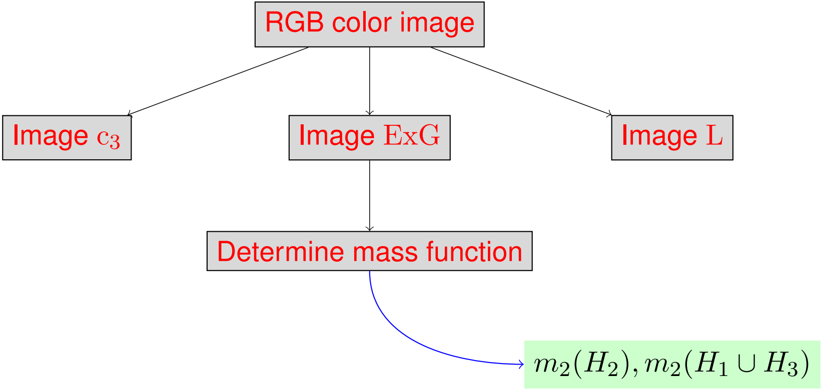

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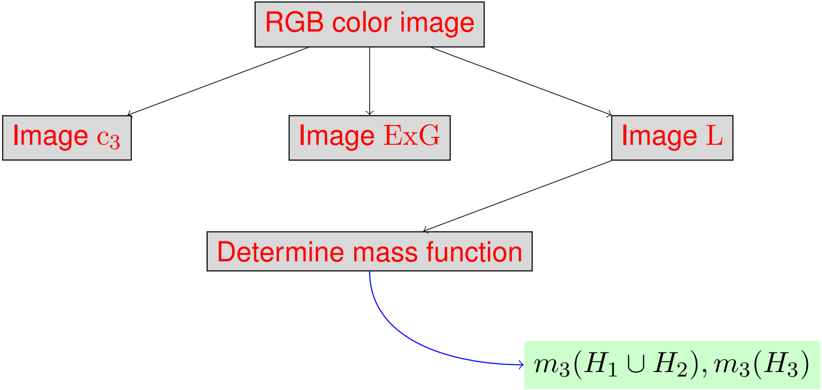

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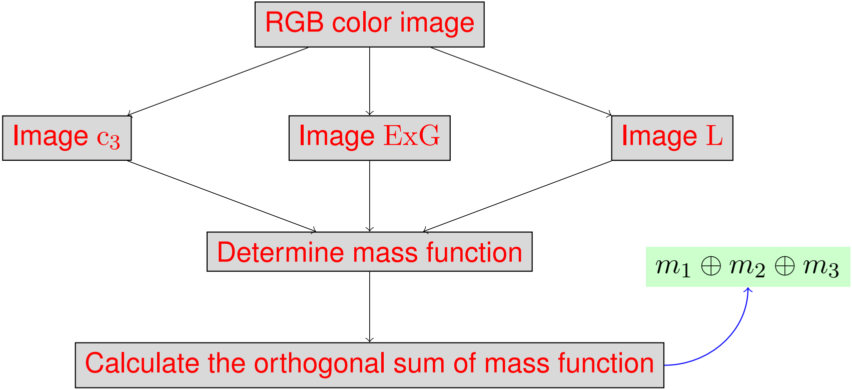

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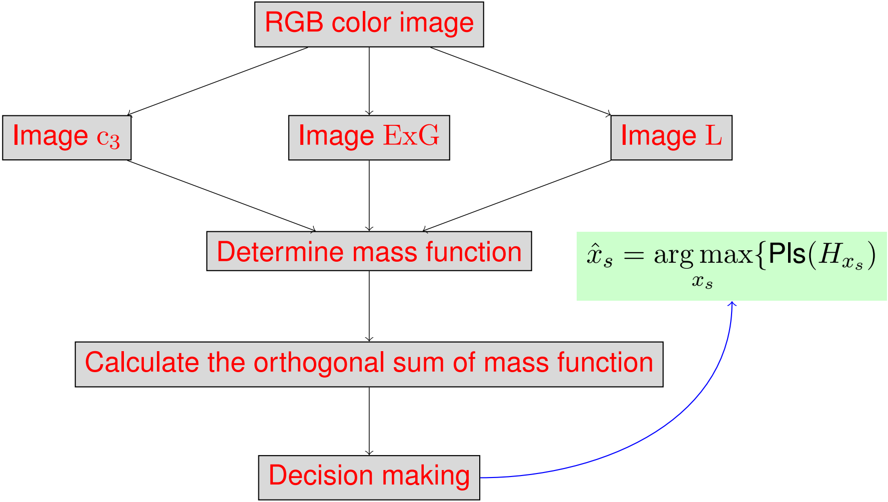


Compute mass function

For each feature image:

- Threshold by Otsu* method for shadow index c_3

Original image

Detected shadow mask

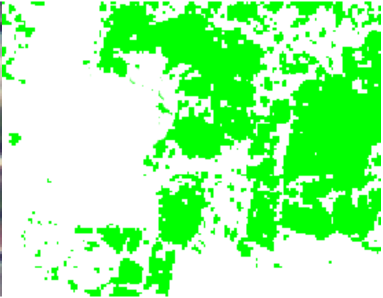
(*)Nobuyuki Otsu, A Threshold Selection Method from Gray-Level Histograms, 1984

Compute mass function

For each feature image:

- Threshold by Otsu* method for vegetation index ExG


Original image


Detected vegetation mask

(*)Nobuyuki Otsu, A Threshold Selection Method from Gray-Level Histograms, 1984

Compute mass function

For each feature image:

- Threshold by Otsu* method for luminance

Original image

Detected dark mask

(*)Nobuyuki Otsu, A Threshold Selection Method from Gray-Level Histograms, 1984

Compute mass function

For each feature image:

- Threshold by Otsu* method for
- Compute mass function using assumption of Gaussian distribution:

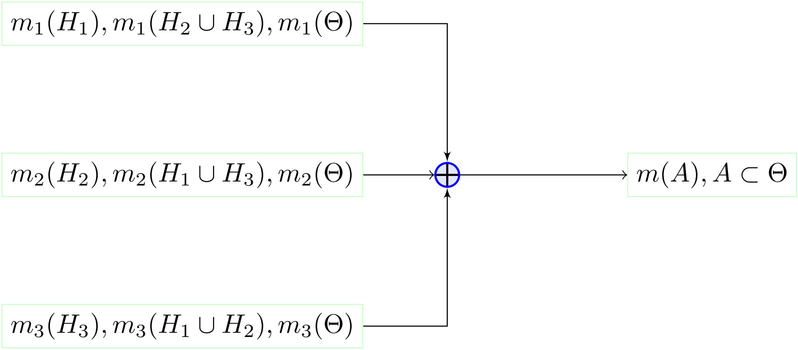
$$m_j(A_i) = \frac{1}{\sigma_i\sqrt{2\pi}}\text{exp}\left(-\frac{(y_s^{(j)}-\mu_i)^2}{2\sigma_i^2}\right)$$

where:

- $j \in \{1,2,3\}$ (3 sources c_3, ExG, L).
- $i \in \{1,2\}$ (2 regions).
- μ_i, σ_i : mean and the variance on the class A_i present in each feature to be fused.

(*)Nobuyuki Otsu, A Threshold Selection Method from Gray-Level Histograms, 1984

Combine different sources

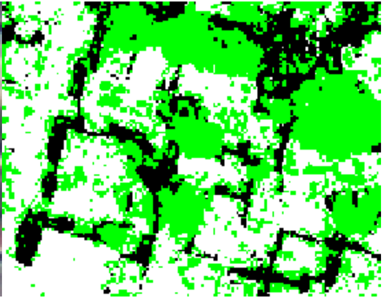


Decision-making

For each pixel s, $x_s \in \{\omega_1, \omega_2, \omega_3\}$, once the mass function of simple hypothesis H_{x_s} is computed:

$$\hat{x}_s = \arg\max_{x_s}\{\text{Pls}(H_{x_s})\}$$

Original image



Detected shadow/vegetation area

Decision-making

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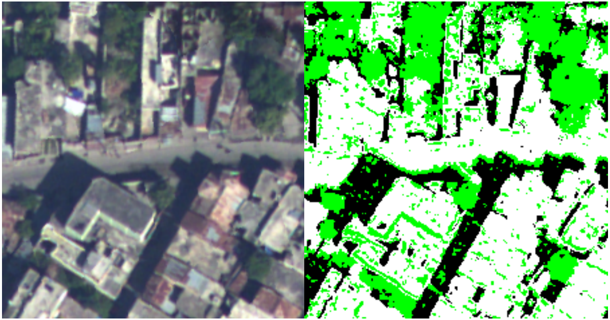

Original image | Detected shadow/vegetation area

Markov random field

- Classifying image pixels into different regions under the constraint of both local observations and spatial relationships.

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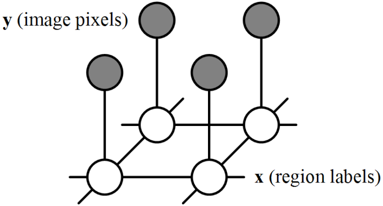
- 

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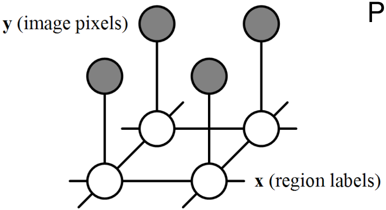
- 

  Probabilistic interpretation:

Markov random field

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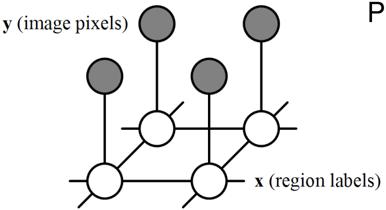
- 

Probabilistic interpretation:

- region labels

$$\hat{x} = \arg\max_{x} p(x | y, \theta)$$

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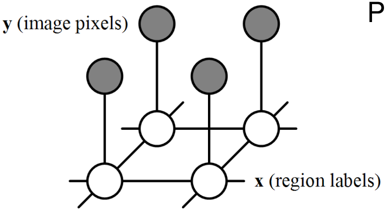
- 

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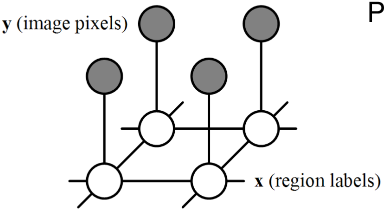
- 

Probabilistic interpretation:

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- image pixels
- model parameters

Iterated conditional modes algorithm (ICM)

$$P(x_s|y, \hat{x}_{\mathcal{S}-\{s\}}) = p(y_s|x_s)p(x_s|\hat{x}_{\mathcal{V}_s})$$

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- Conditional probability: Gaussian distribution
- Prior probability:

$$p(x_s|\hat{x}_{\mathcal{V}_s}) = \frac{1}{Z}\text{exp}\left[-\beta \sum_{l\in\mathcal{V}_s} \delta(x_s - \hat{x}_l)\right]$$

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where:

- δ stands for the Kronecker's delta function.
- $\mathcal{V}_s$ is the set of sites neighbouring s.

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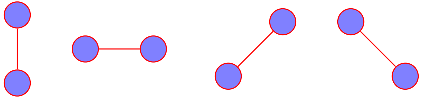

DS evidence theory in Markovian context

Probabilistic framework	Evidential framework

DS evidence theory in Markovian context

Probabilistic framework		Evidential framework
$p(x_s)$	$\longrightarrow$	$[\text{Bel}(H_{x_s}), \text{Pls}(H_{x_s})]$

DS evidence theory in Markovian context

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	$p(x_s)$	$\longrightarrow$	$[\text{Bel}(H_{x_s}), \text{Pls}(H_{x_s})]$
Likelihood	$p(y_s \mid x_s)$	$\longrightarrow$	$m_s(A), H_{x_s} \subseteq A$

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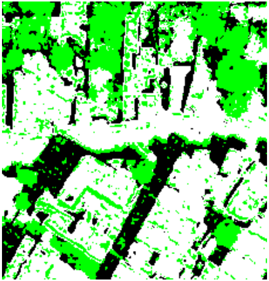
$$m_1 \oplus m_2 \oplus m_3$$



DS evidence theory in Markovian context

	Probabilistic framework		Evidential framework
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Likelihood	$p(y_s \mid x_s)$	$\longrightarrow$	$m_s(A), H_{x_s} \subseteq A$
Conditional probability	$p(x_s \mid \hat{x}_{\mathcal{V}_s})$	$\longrightarrow$	$m_s(A \mid \hat{x}_{\mathcal{V}_s}), H_{x_s} \subseteq A$

DS evidence theory in Markovian context

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Conditional probability	$p(x_s \mid \hat{x}_{\mathcal{V}_s})$	$\longrightarrow$	$m_s(A \mid \hat{x}_{\mathcal{V}_s}), H_{x_s} \subseteq A$
Posterior probability	$p(x_s \mid y, \hat{x}_{\mathcal{S}-\{s\}})$	$\longrightarrow$	$M_s(A) = m_s(A) \oplus m_s(A \mid \hat{x}_{\mathcal{V}_s})$

DS evidence theory in Markovian context

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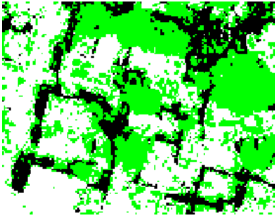
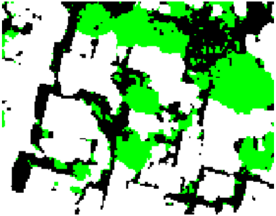
	$p(x_s)$	$[\text{Bel}(H_{x_s}), \text{Pls}(H_{x_s})]$
Likelihood	$p(y_s \mid x_s)$	$m_s(A), H_{x_s} \subseteq A$
Conditional probability	$p(x_s \mid \hat{x}_{\mathcal{V}_s})$	$m_s(A \mid \hat{x}_{\mathcal{V}_s}), H_{x_s} \subseteq A$
Posterior probability	$p(x_s \mid y, \hat{x}_{\mathcal{S}-\{s\}})$	$M_s(A) = m_s(A) \oplus m_s(A \mid \hat{x}_{\mathcal{V}_s})$
Decision making	$\hat{x}_s = \arg\max_{x_s} p(x_s \mid y, \hat{x}_{\mathcal{S}-\{s\}})$	$\hat{x}_s = \arg\max_{x_s} \text{Pls}(H_{x_s})$

Qualitative evaluation

Original image

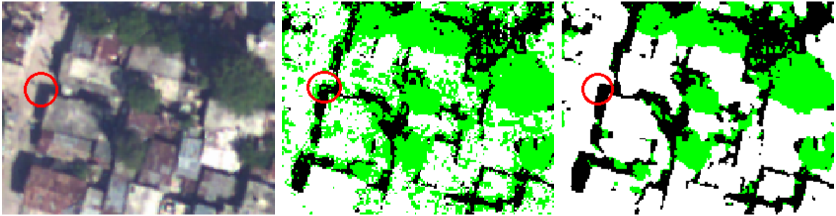


DS fusion



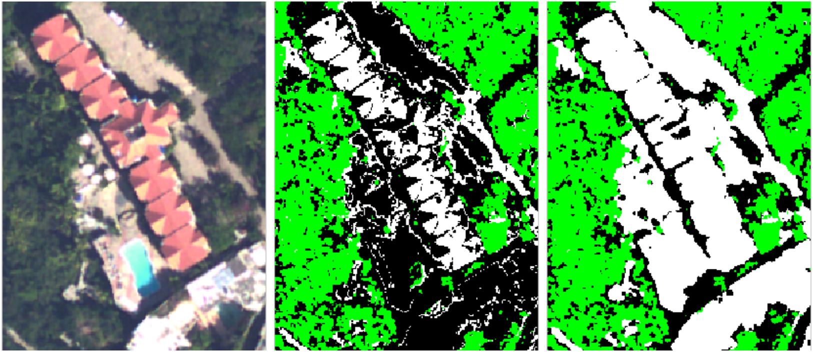
DS fusion + MRF

Qualitative evaluation



Original image DS fusion DS fusion + MRF

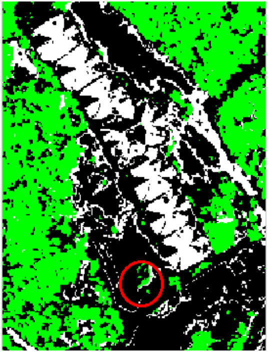
Qualitative evaluation



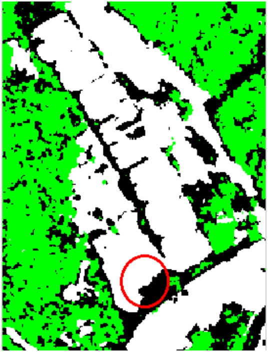
Original image | DS fusion | DS fusion + MRF

Qualitative evaluation

Original image



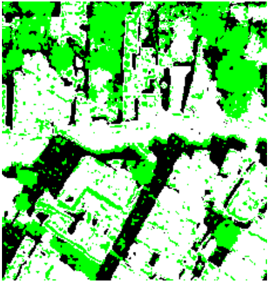
DS fusion

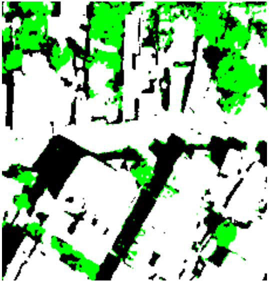


DS fusion + MRF

Qualitative evaluation


Original image


DS fusion


DS fusion + MRF

Qualitative evaluation

Original image

DS fusion

DS fusion + MRF

Conclusion

- Introduces a new scheme to simultaneously detect shadow regions and vegetation regions.
- DS evidence theory combine different shadow indices and vegetation indices and estimate the imprecision and uncertainty of information.
- Contextual information is taken into account using MRF.
- Applied successfully on color aerial images with different scenes: urbain and rural.

Thank you for your attention!
Question?