A Metrological Measurement of Texture in Hyperspectral Images using Relocated Spectral Difference Occurrence Matrix

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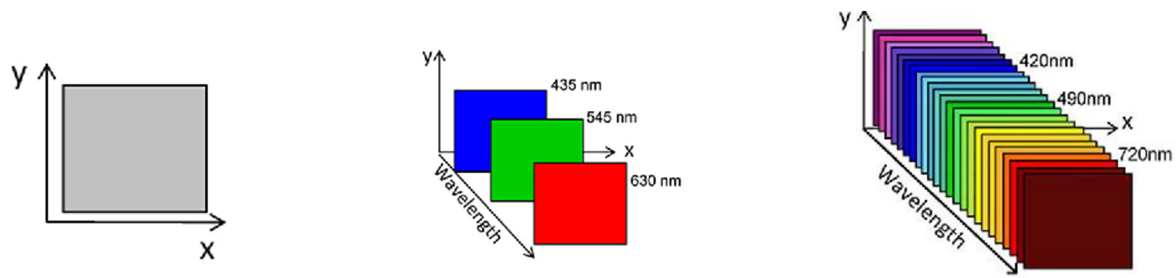
Outline

Introduction

Why metrology?

- Metrology → science of measurement
- Hyperspectral imaging → dense spectral sampling
  - measurement of surface physical / optical properties
  - direct relationship between image and physical content
- Complete physical meaning to be preserved
  - accuracy, uncertainty and bias are quantifiable



(a) (b) (c)

FIGURE 1* - (a) Gray-scale, (b) color, (c) hyperspectral image

* Adapted from Li, Q., He, X., Wang, Y., Liu, H., Xu, D., and Guo, F., "Review of Spectral Imaging Technology in Biomedical Engineering: Achievements and Challenges," J. Biomed. Opt., 18, 10 (2013).

Overview of texture analysis

- State of the art: co-occurrence matrix [1], local binary pattern [2] etc.
  - originally developed for grayscale images
- Adaptation for hyperspectral images with L bands → **metrologically invalid**
  - cross-channel processing [3]
  - band-by-band (marginal) processing [3]

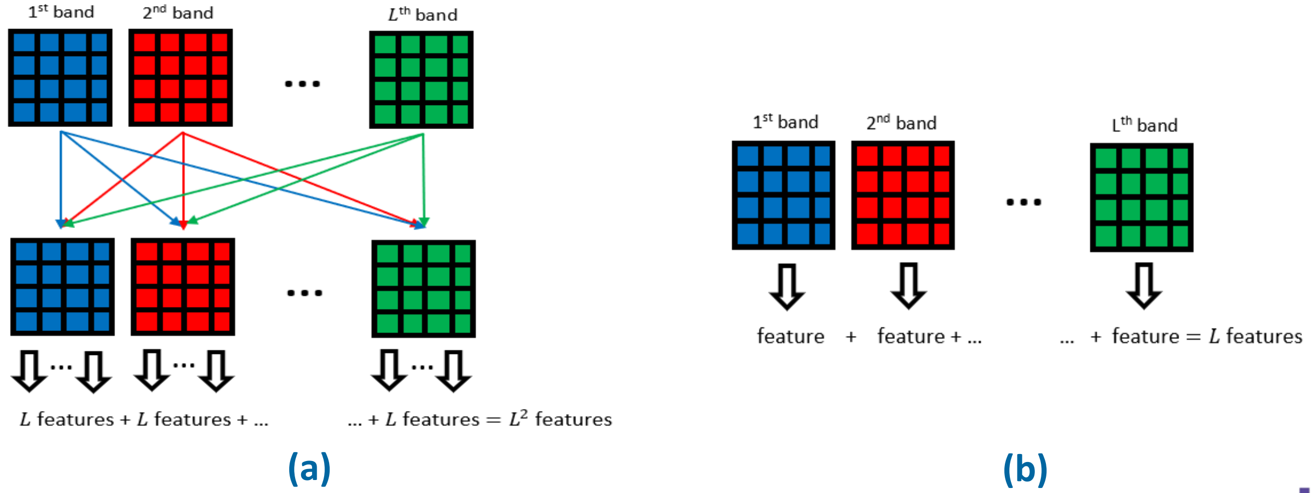


FIGURE 2 – (a) Cross-channel, (b) band-by-band

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Problems of hyperspectral texture analysis

- Curse of dimensionality
  - band selection [4,5,6], dimensionality reduction [7,8,9]
  - result dependent on data → incomparable
- Spectrum → continuous function $f(\lambda)$ over the wavelength λ
  - hyperspectral acquisition → discrete sequence $S = \{s(\lambda), \forall\lambda[\lambda_{min}, \lambda_{max}]\}$
  - spectral bands → highly correlated, not independent
  - vectorial representation, L2-norm → not adapted

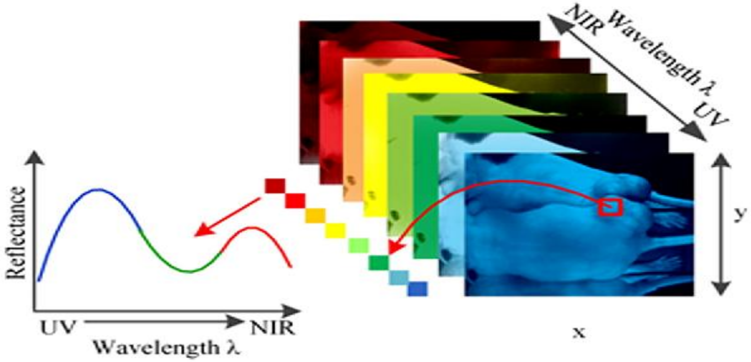

FIGURE 3* - Hyperspectral acquisition: continuous → discrete

* Adapted from Lu, G., and Fei, B., "Medical Hyperspectral Imaging: A Review," Journal of Biomedical Optics, 19, 1 (2014).

Defining texture

Defining hyperspectral texture as …

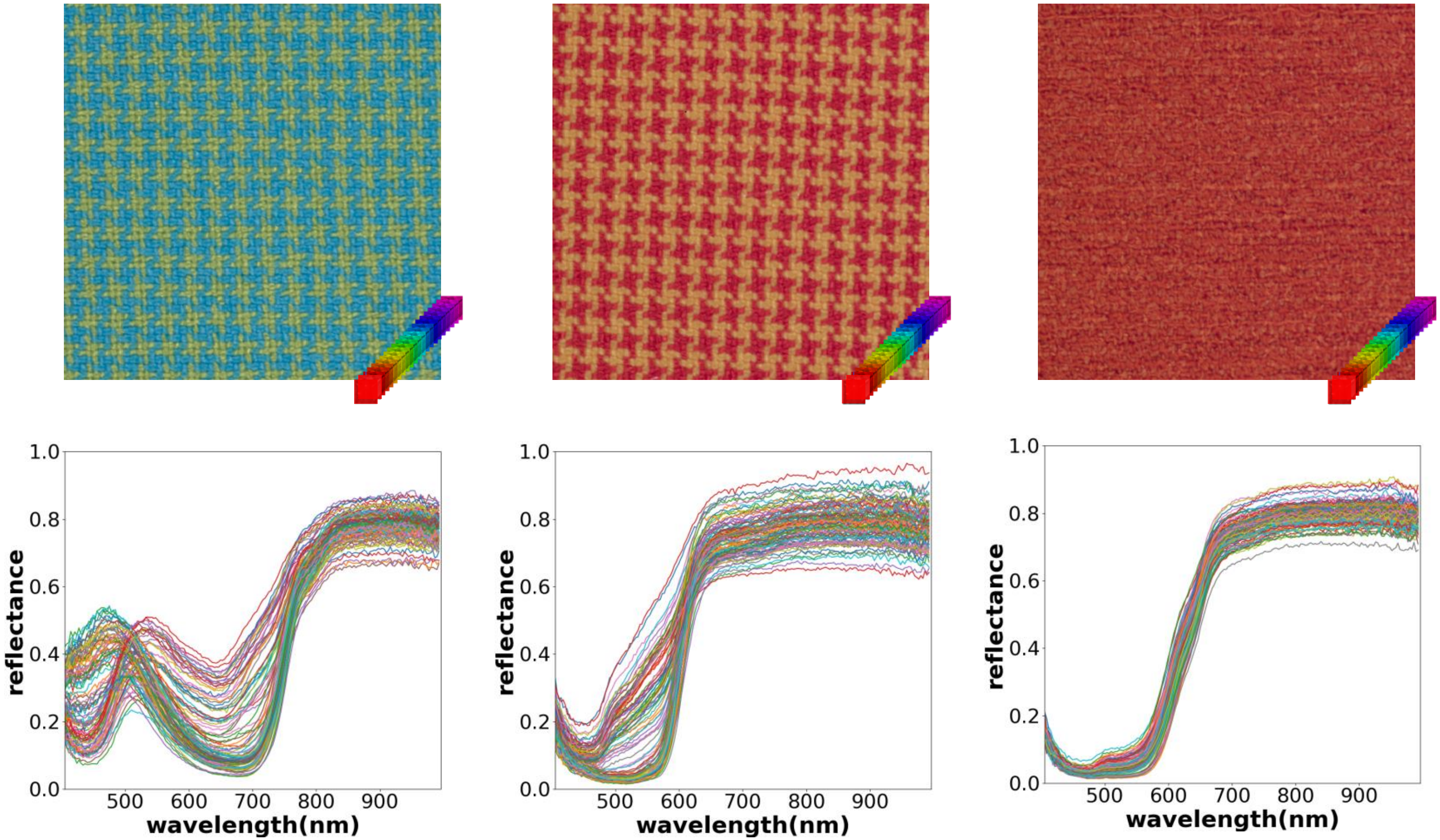

FIGURE 4 - Sample spectra from texture

… a joint spectral and spatial distribution.

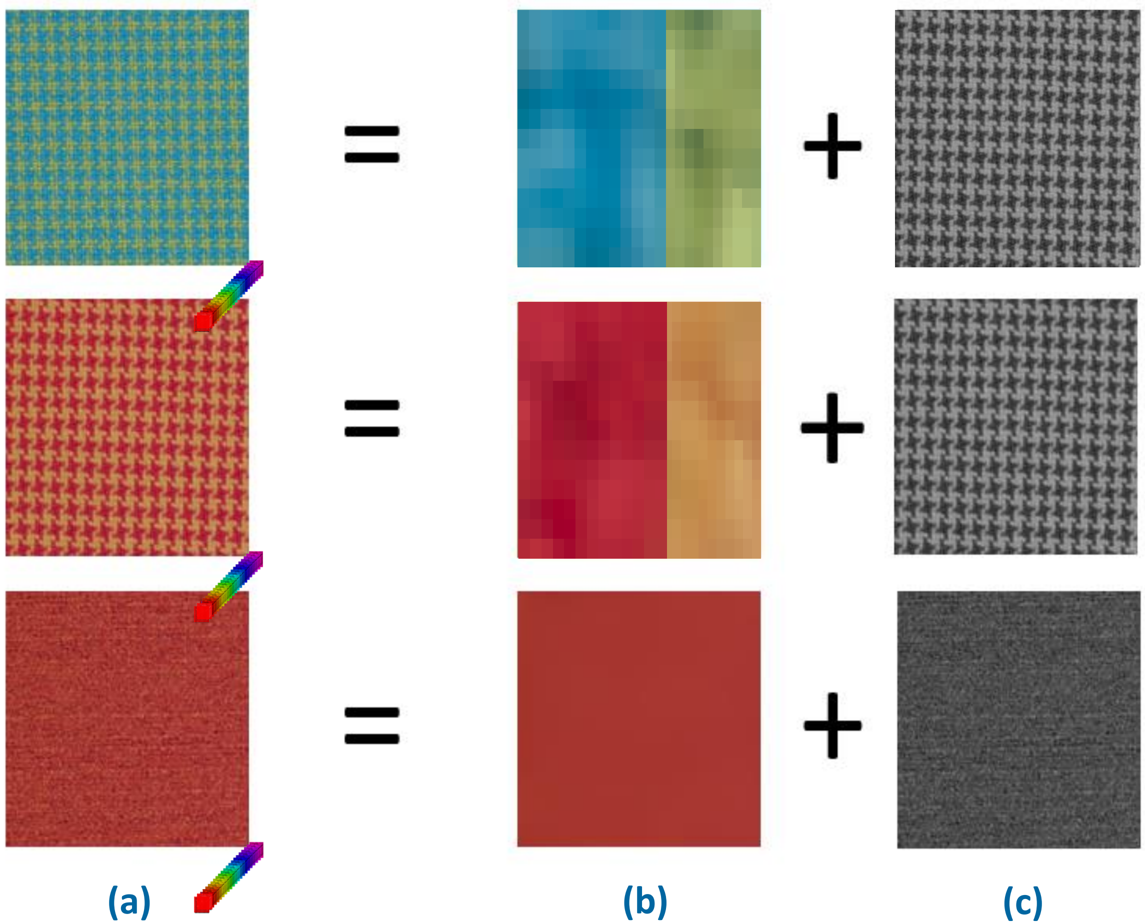

FIGURE 5 – (a) Texture = (b) spectral + (c) spatial distribution

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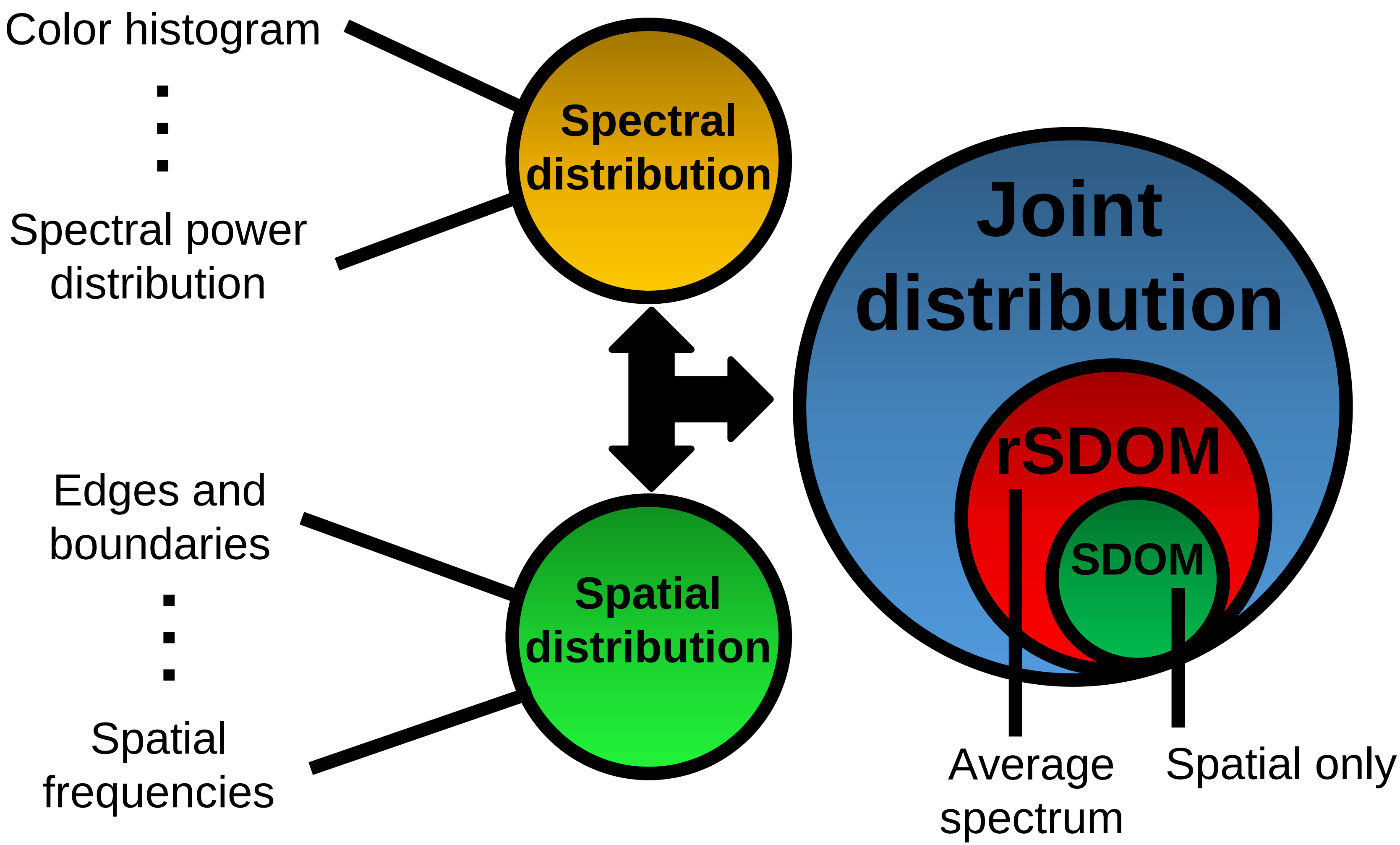


FIGURE 6 – rSDOM in proposed texture definition

Hyperspectral texture feature

From psychophysical research to application

- Julesz conjecture: texture discrimination from low-order statistics [10]
  - probability of a chosen point having certain value → spectral distribution
  - probability of two chosen points having certain values → spatial distribution

- Co-occurrence matrices → distribution of pixel pairs defined by an offset $\vec{v}$

$\vec{v}$

1	1	5	6	8
2	3	5	1	2
4	5	1	2	2
8	5	1	2	5

(a)

i \ j	1	2	3	4	5	6	7	8
1	1	3	0	0	1	0	0	0
2	0	1	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	3	0	0	0	0	1	0	0
6	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

(b)

FIGURE 7 – (a) Gray-scale image → (b) co-occurrence matrix

Approximation by sum and difference histograms

- Original definition → impractical for hyperspectral image
  - Unser [11]: approximation by sum (spectral) and difference (spatial) histograms
- Full-band processing → spectral difference of pixel pair
  - band selection, dimensionality reduction → not required
  - analysis independent from spectral count → **metrological approach**

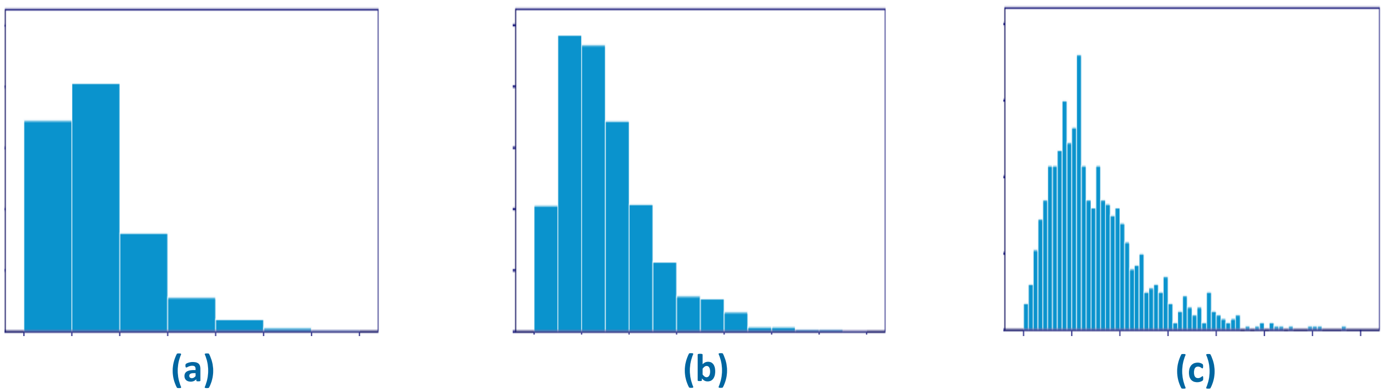
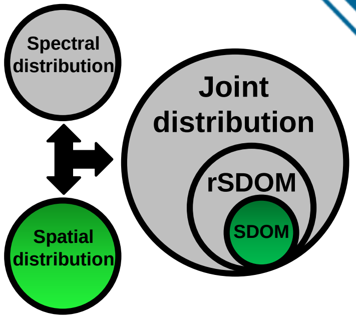


FIGURE 8 – Illustrations of histogram from:
(a) gray-scale, (b) color, (c) hyperspectral image

Describing spatial distribution: Spectral Difference Occurrence Matrix



1. Define $\vec{v}$ with distance l and orientation θ
2. Determine pixel pairs (S_i, S_j) with $\vec{v}$
3. Express spectral difference ΔS of all pairs as probability distribution

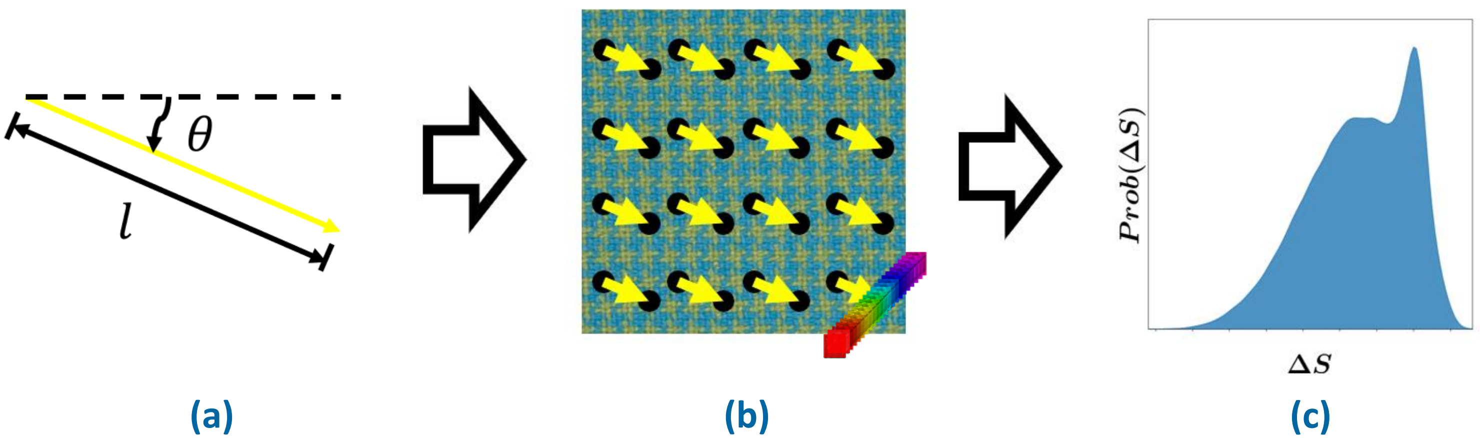
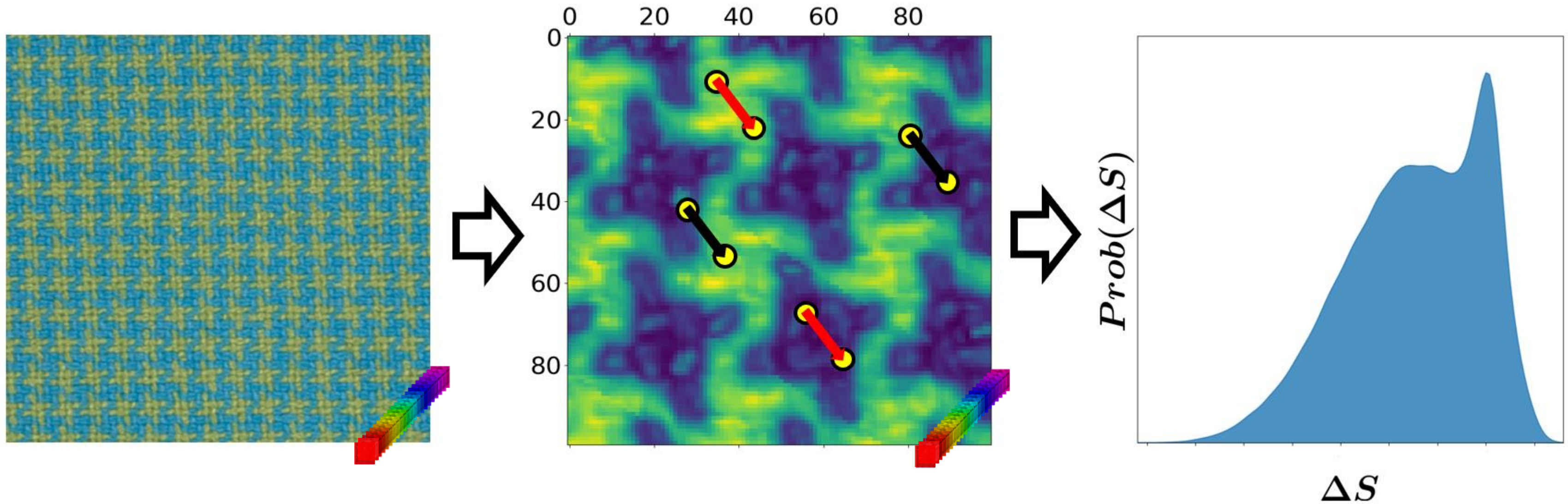


FIGURE 9 – Calculating SDOM: (a) pick $\vec{v}$, (b) pixel pairs, (c) spectral difference → probability distribution

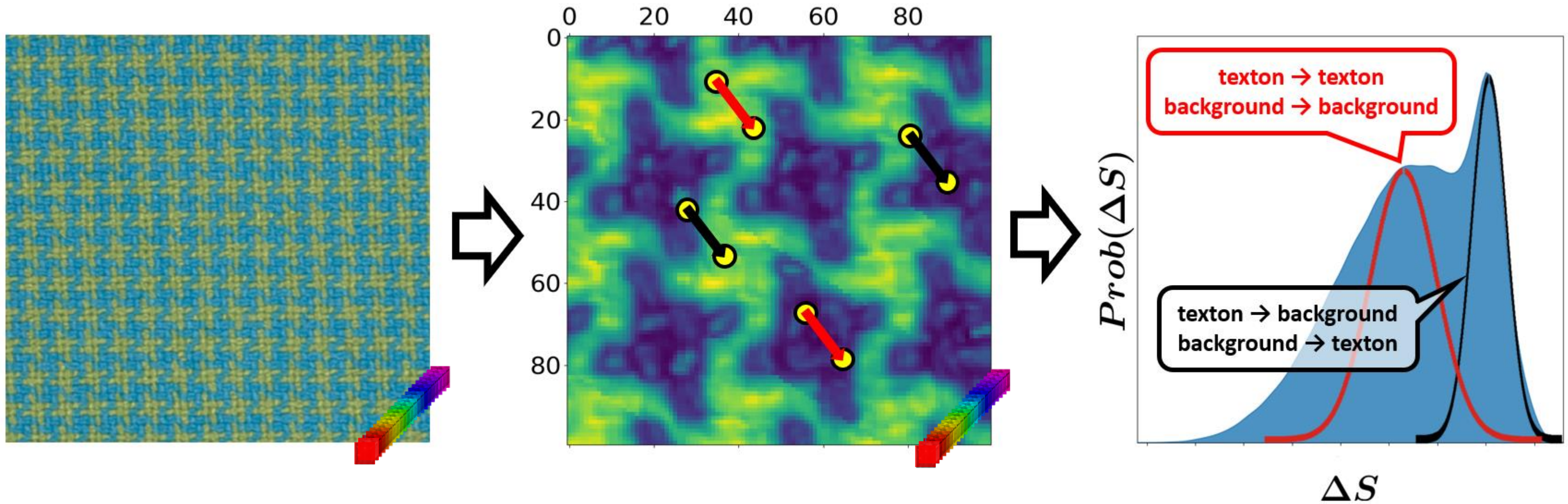
SDOM: a working example



(a) (b) (c)

FIGURE 10 – (a) Texture; (b) magnified: texton (yellow), background (cyan), (c) SDOM

SDOM: a working example



(a) (b) (c)

FIGURE 10 – (a) Texture; (b) magnified: texton (yellow), background (cyan), (c) SDOM

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SDOM: more examples

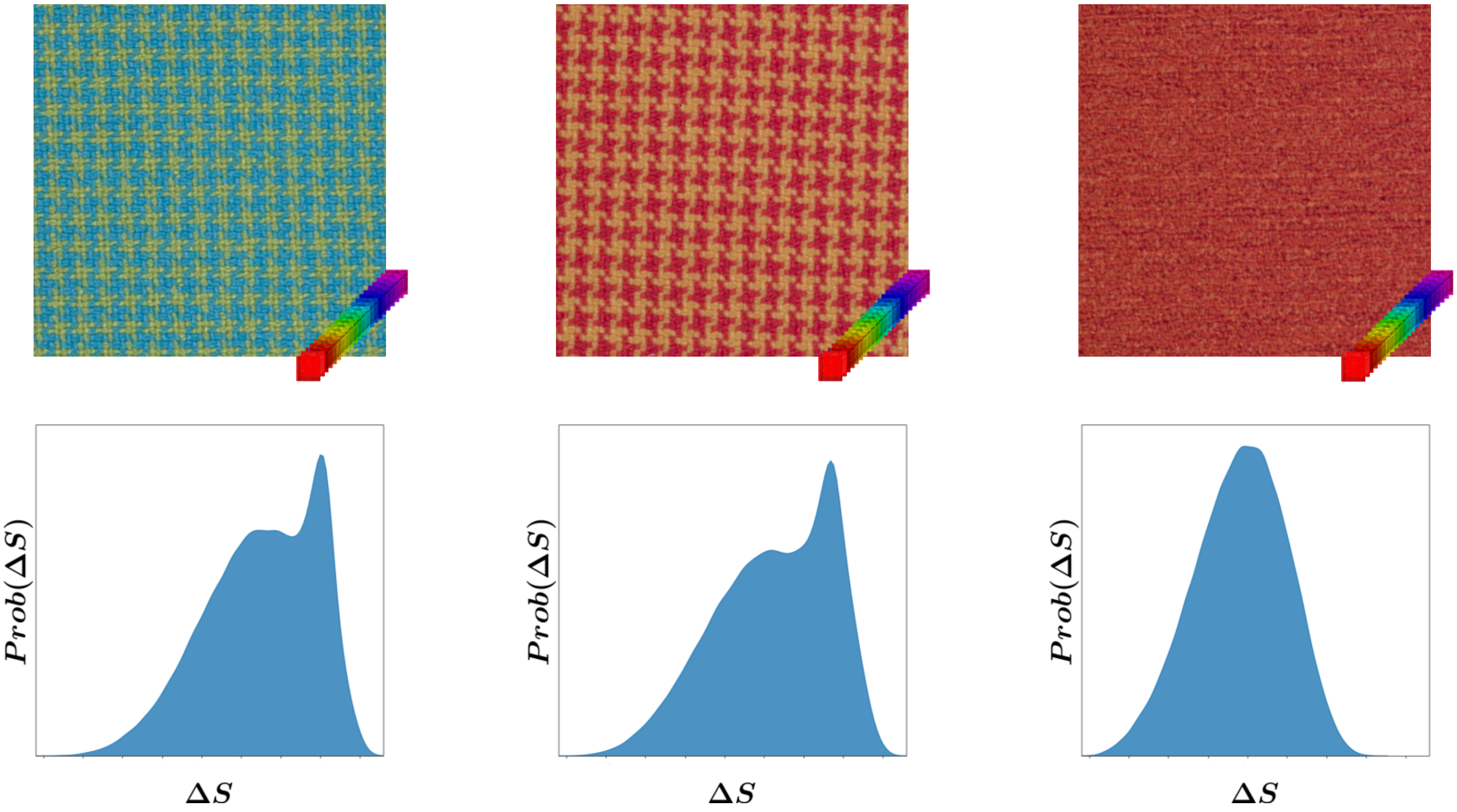

FIGURE 11 – More SDOM examples

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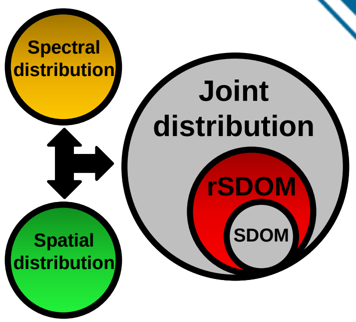
Spectral-spatial analysis: Relocated Spectral Difference Occurrence Matrix



- Spectral distribution → average spectrum S_μ
- SDOM shifted with ΔS_μ between texture → rSDOM

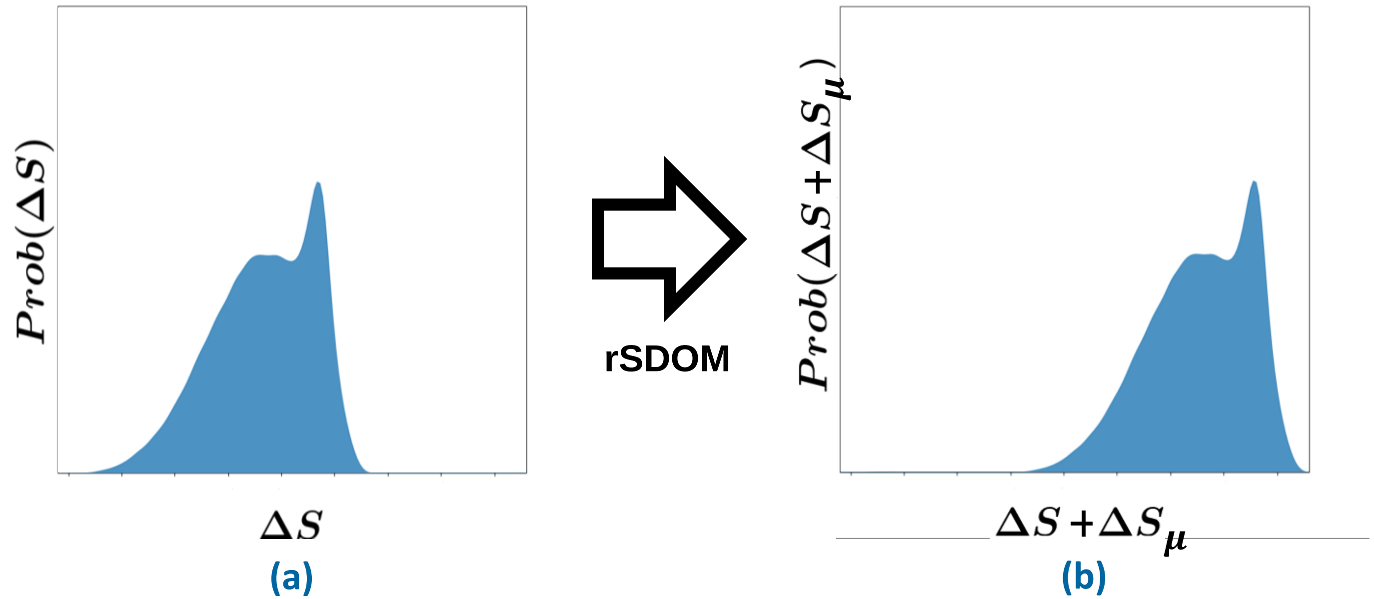


FIGURE 12 – Illustrations for (a) SDOM, (b) rSDOM

Metrological calculation of spectral difference

- Kullback-Leibler pseudo-divergence (KLPD) [12]
  - considers spectrum as function → **metrologically valid**
  - separates spectral shape ΔG and intensity difference ΔW
  - rSDOM → 2D probability distribution
  - not limited to any spectral difference formula

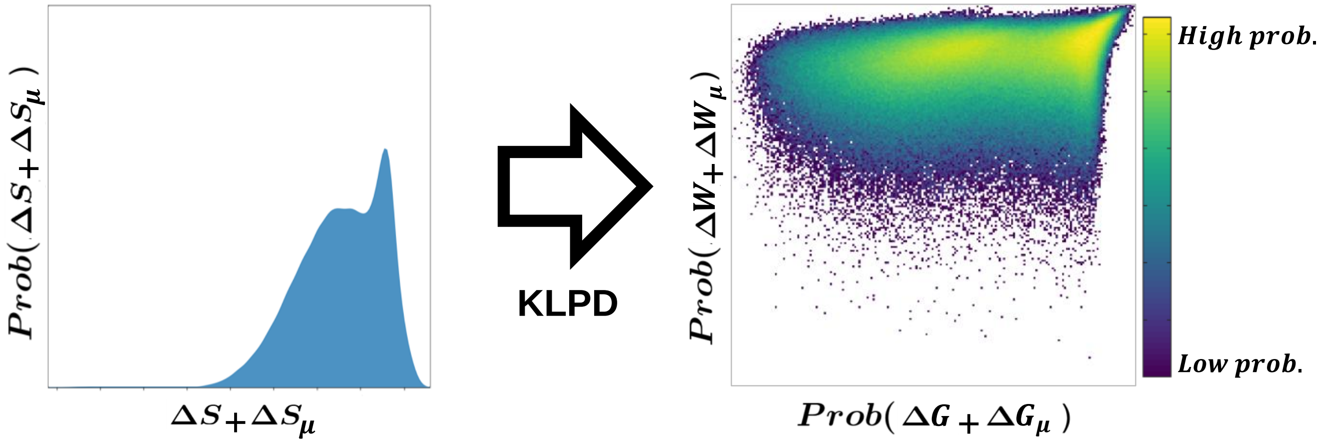


FIGURE 13 – (a) General formulation, (b) with KLPD

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Experiment and analysis

Texture classification on HyTexiLa [3] dataset

- 112 textured images, spectral range: 405.37 nm - 995.83 nm (186 bands)
- Each image split into 25 patches → training: 12, testing (classification): 13

FIGURE 14 – Samples from HyTexiLa

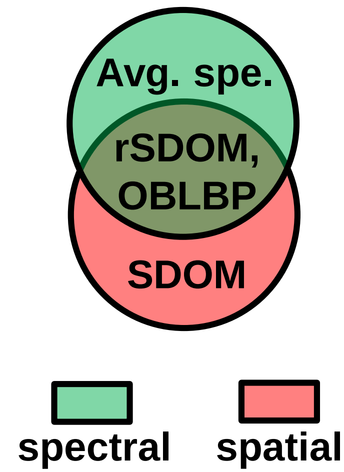
Classification accuracy

- Classification with 10 trials → results averaged
  - calculated with $l = 3, \theta = 0$ (mono-scale, mono-direction)

- Compared with opponent band local binary patterns (OBLBP) [18]
  - calculated with $l = 1$ with $P = 8$ neighbors (multi-direction)
  - cross-channel processing on 18 selected channels

Method	Accuracy (%)	Metrology
Average spectrum	92.0 ± 0.2	-
SDOM	62.1 ± 0.3	-
rSDOM	94.7 ± 0.1	✓
OBLBP	98.76	✗

TABLE 1 – Comparison of classification accuracy



Discussion

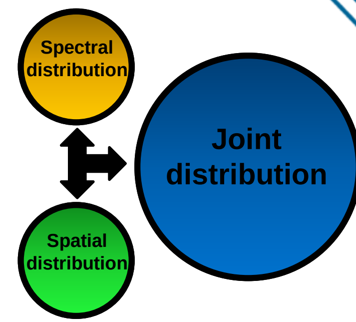
- rSDOM → excellent performance
  - misclassification mainly in wood and vegetation images
  - average spectrum → partial spectral analysis
  - texture directionality and scale variability not considered
- Limitation induced by Gaussian modelling of rSDOM
  - in return for smaller feature
- For image with N pixels, L bands, assessment in P directions and $\tilde{L}$ bands:

rSDOM	Aspect	OBLBP
$L+6$	Feature size	$\tilde{L}^2 \cdot 2^P$
$\mathcal{O}(N \cdot L)$	Complexity	$\mathcal{O}\left(N \cdot P \cdot 2^{\tilde{L}}\right)$

TABLE 2 – Comparison of feature size and complexity

Conclusion

A new metrological texture concept



- ***Generic*** formulation: independent of sensor resolution
  - applicable for gray-scale, color images
- ***Metrological*** construction: operation in difference space
  - full band processing → all physical meaning preserved
- ***Adaptive*** feature: separation of spectral and spatial dimension
  - for invariance to light changes, use SDOM
- ***Efficient*** description and discrimination
  - small feature size and low complexity
- Future work since ICIP
  - analysis with full spectral distribution (RSDOM, accepted into WHISPERS 2019)
  - multi-scale and multi-direction feature

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