Texture features extracted from multispectral images acquired under uncontrolled illumination conditions. Application to precision farming

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Dr. Benjamin Mathon

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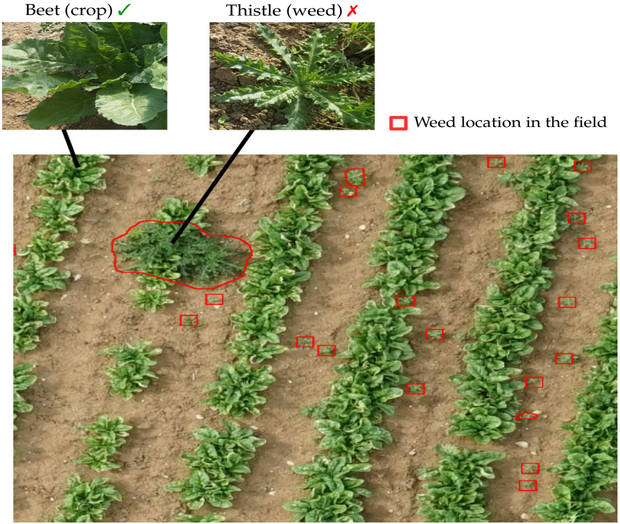
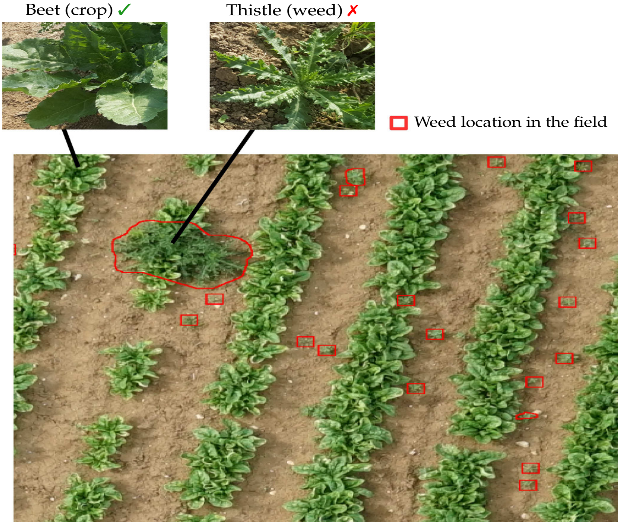


Aerial view of a beet crop field infested by thistle weed[1]

[1] M. D. Bah, Détection des adventices par imagerie aérienne, PhD thesis, Université d'Orléans, France, 2020.



Aerial view of a beet crop field infested by thistle weed[1]

- Weeds (unwanted plants) strongly compete with crops in light, water, and nutrients

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How?

- Manual weeding

✓Ecological
✗ Labor-intensive, time-consuming
✗ Difficult for large crop fields

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✓ Effective in killing weeds
✓ Time-efficient
✗ Toxic

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Selective weed spraying

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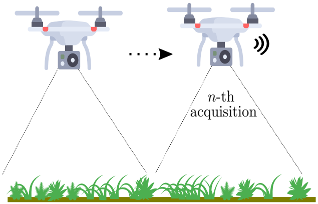
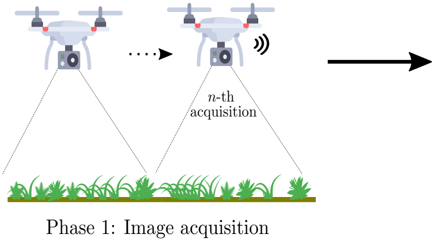
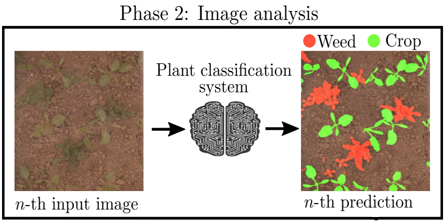


Phase 1: Image acquisition

Selective weed spraying





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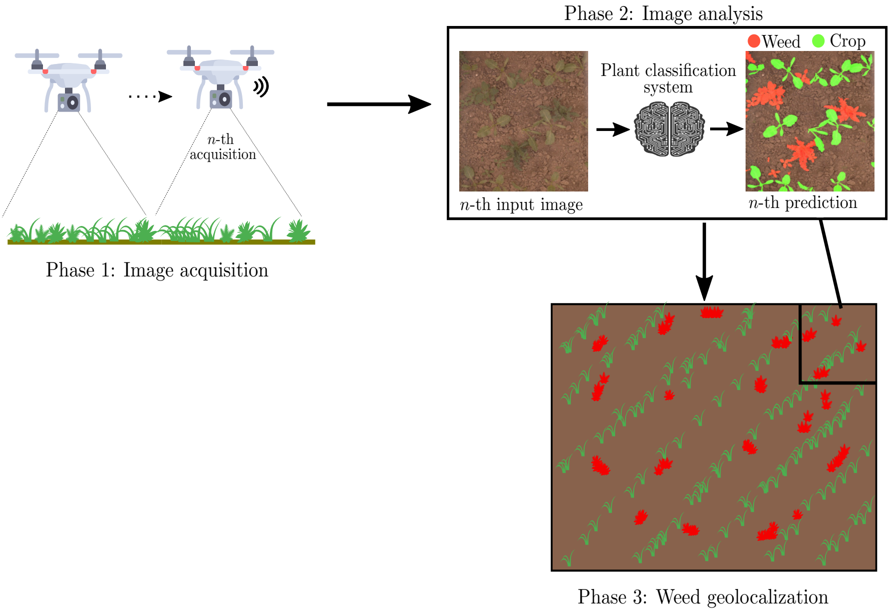

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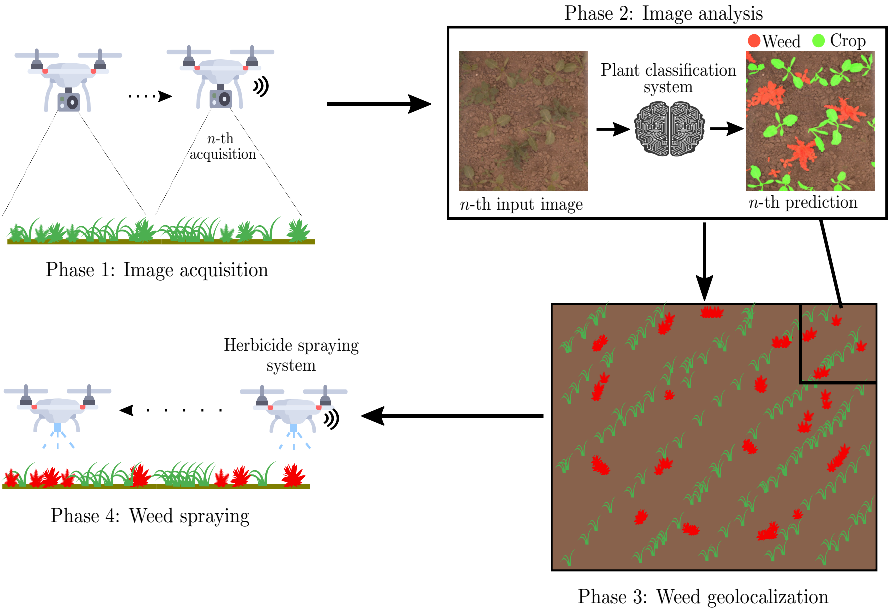

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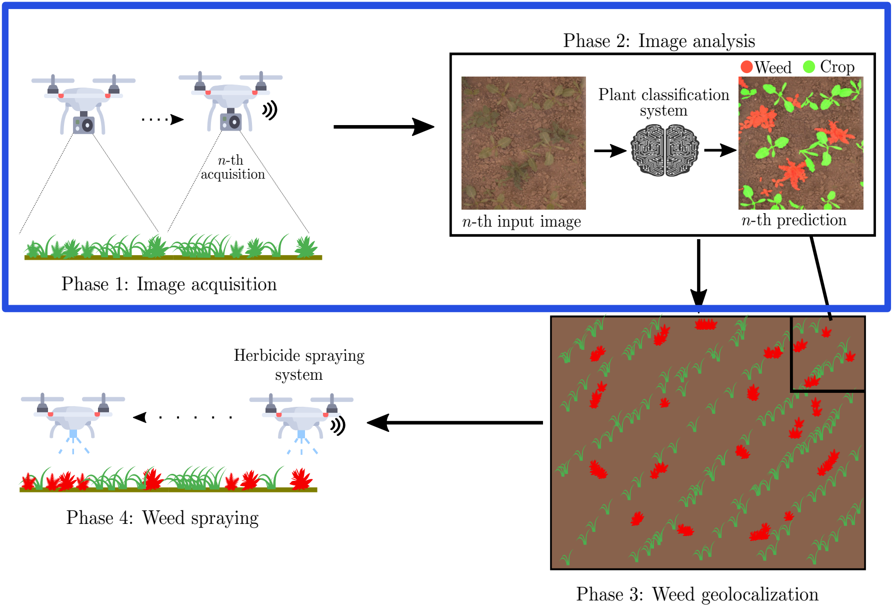

Forefront Plant sectors in the Hauts-de-France region in 2020[1]

		Production rank in France
	Wheat	1st
	Barley	3rd
	Sugar beet	1st
	Chicory Textile linen	1st 3rd
	Potato	1st
	Endive	1st
	Peas	1st
	Green bean	1st
	Carrots	2nd
	Onions	2nd

Considered plants

1. **Crops**: sugar beet (betterave sucrière), wheat (blé), and green bean (haricot vert)
2. **Weeds**: thistle (chardon), goosefoot (chénopode), and datura (datura)

[1] https://draaf.hauts-de-france.agriculture.gouv.fr/IMG/pdf/MEMENTO_32P_105x155-BAT1_cle8ddda4.pdf

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Experimental greenhouse (Chuignes 80340, France)

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Challenges

Some weeds look like crop

Weed (datura); other plants: crop (bean)

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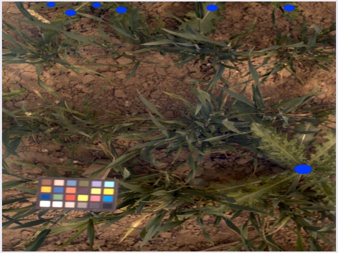
Plant occlusion



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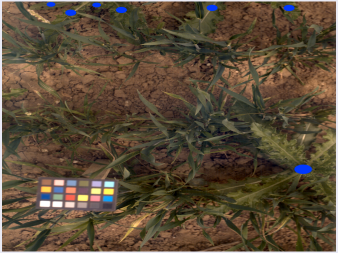
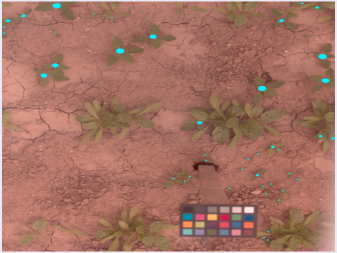


Weed (thistle); other plants: crop (wheat)

Different growth stages

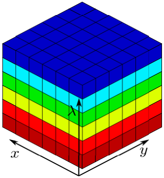


Weed (goosefoot); other plants: crop (beet)

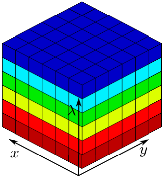
Overview

1. Multispectral acquisition devices
2. Multispectral image acquisition
3. Reflectance estimation
4. Texture features
5. Conclusion and perspectives

Overview



(a) Multispectral image



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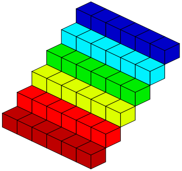
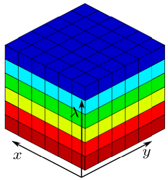


(b) Linescan camera

1. Multishot (b):



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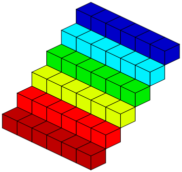
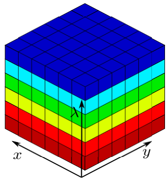


(b) Linescan camera

1. Multishot (b):
   - Requires several seconds to build the multispectral image
   - Sensitive to illumination variation



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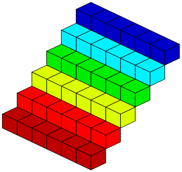

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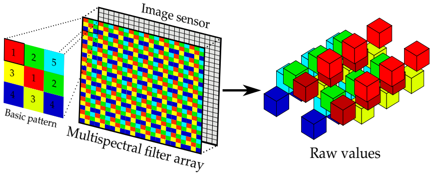

(c) MSFA-based camera

1. Multishot (b):
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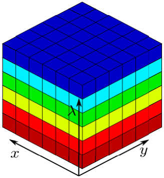
2. Snapshot based on multispectral filter array (MSFA) technology (c):



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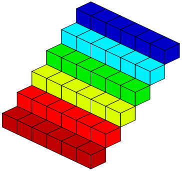

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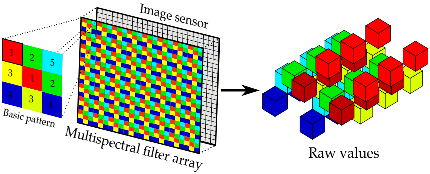

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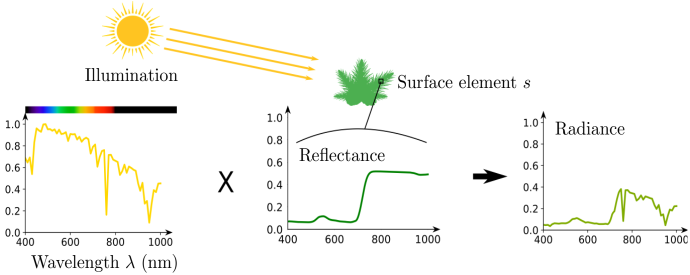
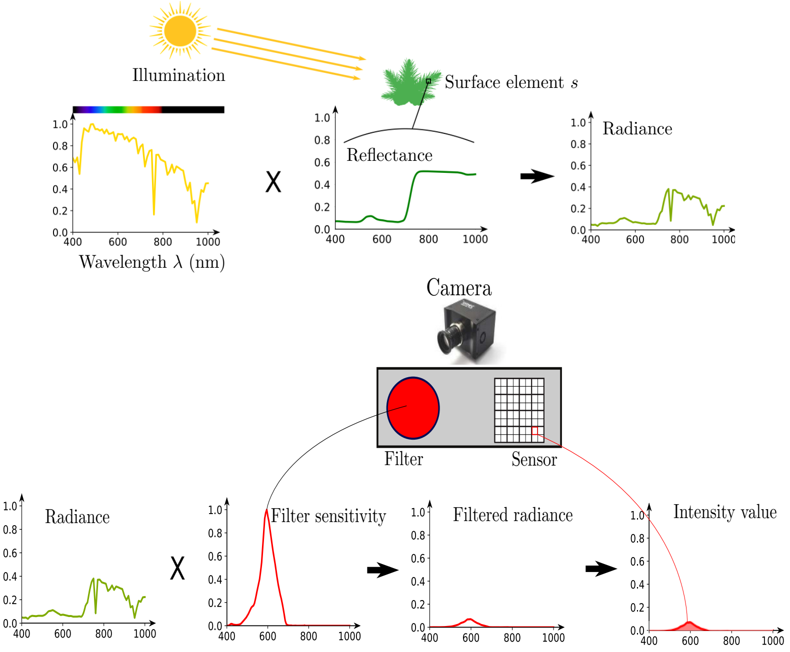
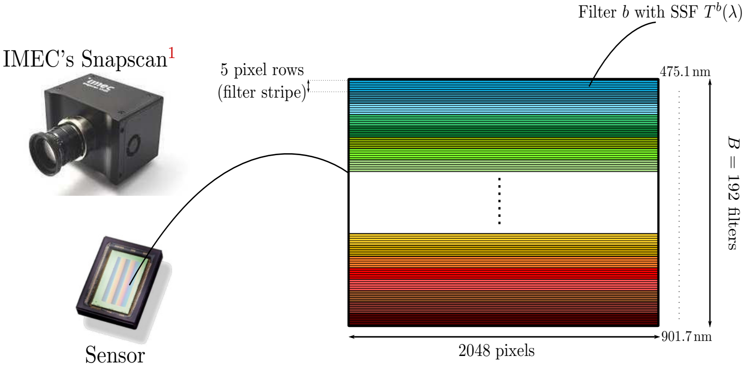
   - Requires demosaicing to estimate the fully-defined multispectral image
   - Limited number of channels


Illumination
Surface element s
Reflectance
Radiance
X
Wavelength λ (nm)
1.0
0.8
0.6
0.4
0.2
0.0
400
600
800
1000


Illumination
Wavelength λ (nm)
X
Surface element s
Reflectance
Radiance
Camera
Filter
Sensor
Radiance
X
Filter sensitivity
Filtered radiance
Intensity value

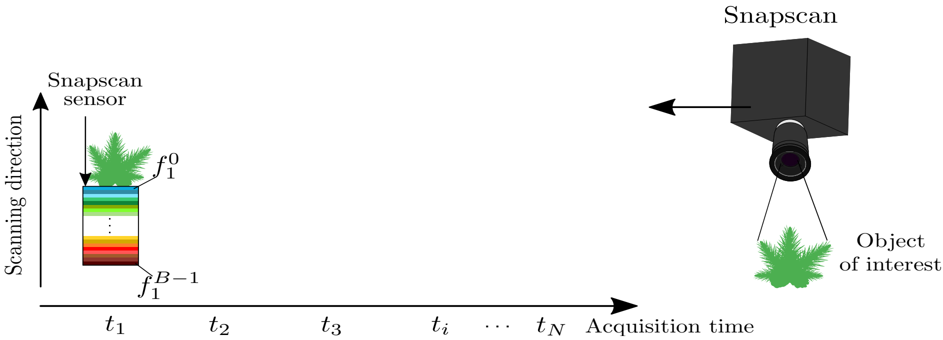
Overview

The Snapscan camera



[1] J. Pichette *et al.*, Fast and compact internal scanning CMOS-based hyperspectral camera: the Snapscan, Proceedings of the SPIE Electronic Imaging Annual Symposium: Photonic Instrumentation Engineering IV, 2017.

Frame acquisition and radiance image assembly



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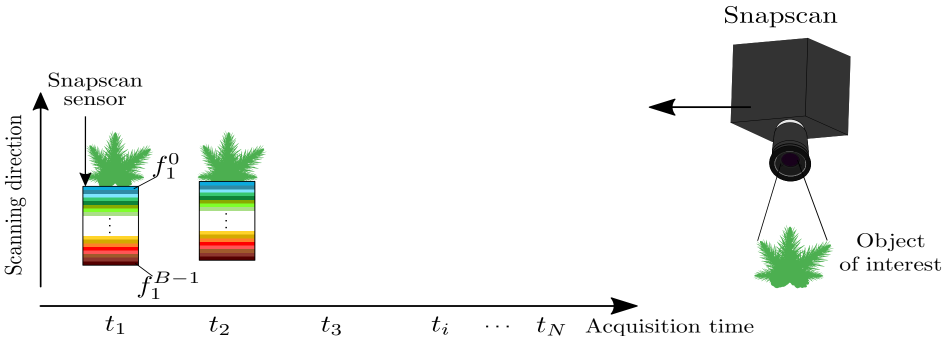

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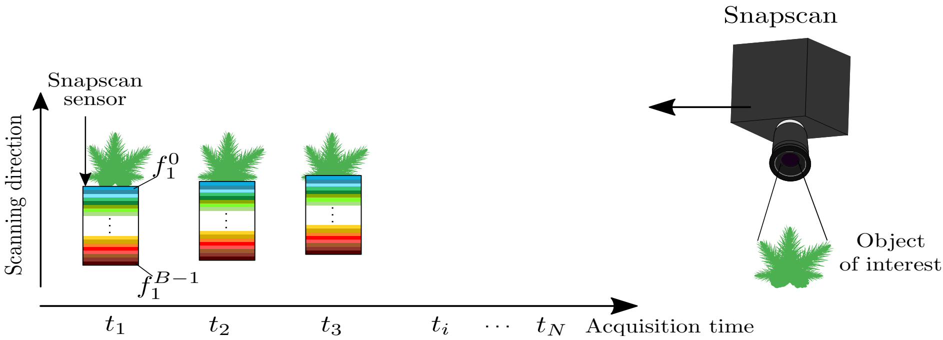

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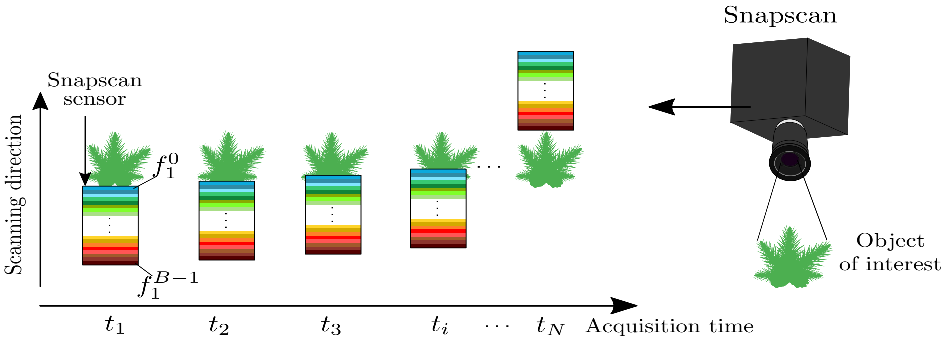

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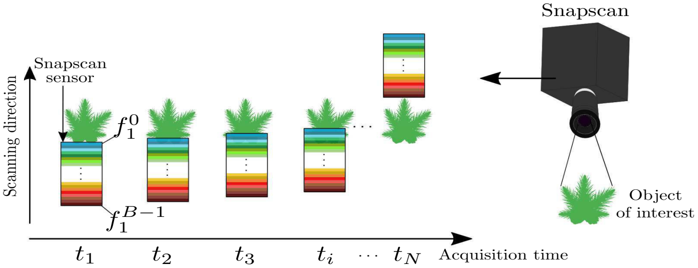
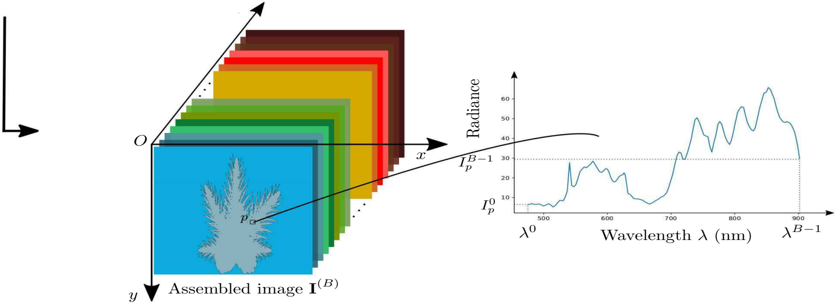
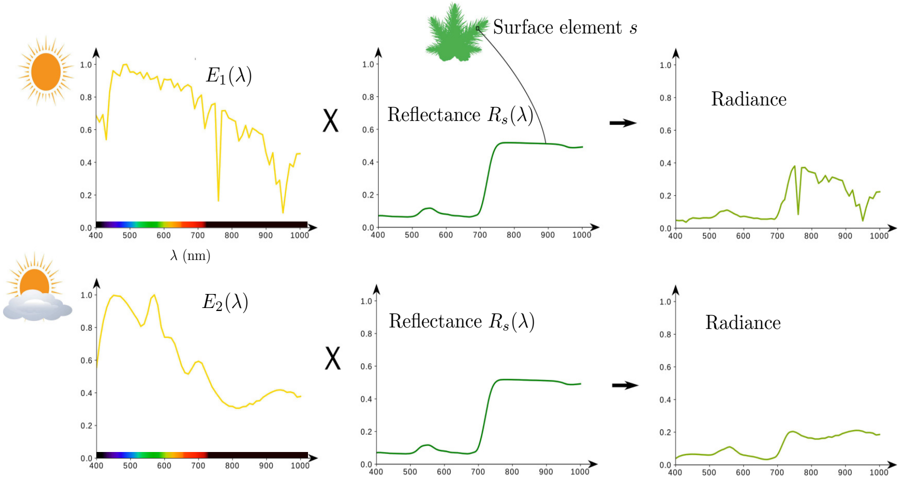




Radiance is illumination-dependant



Solution → Estimate reflectance to be invariant to illumination conditions

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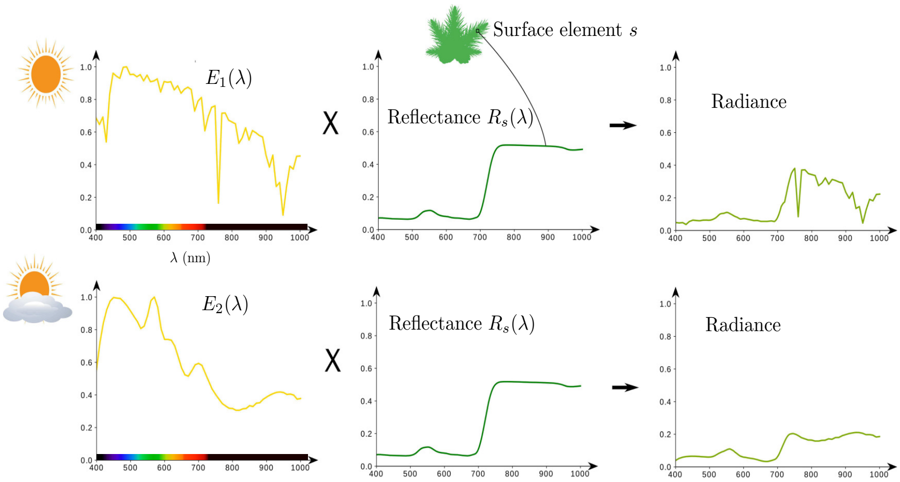

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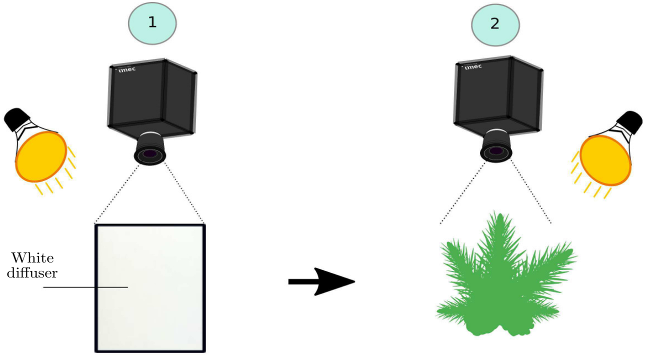
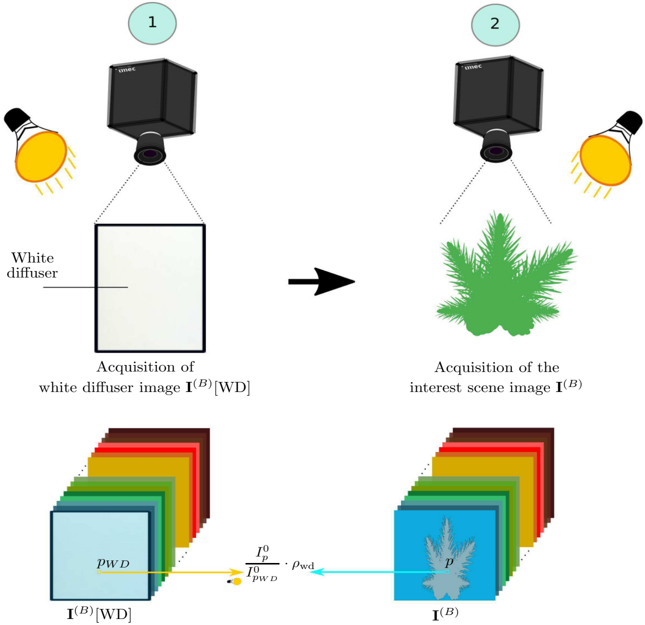
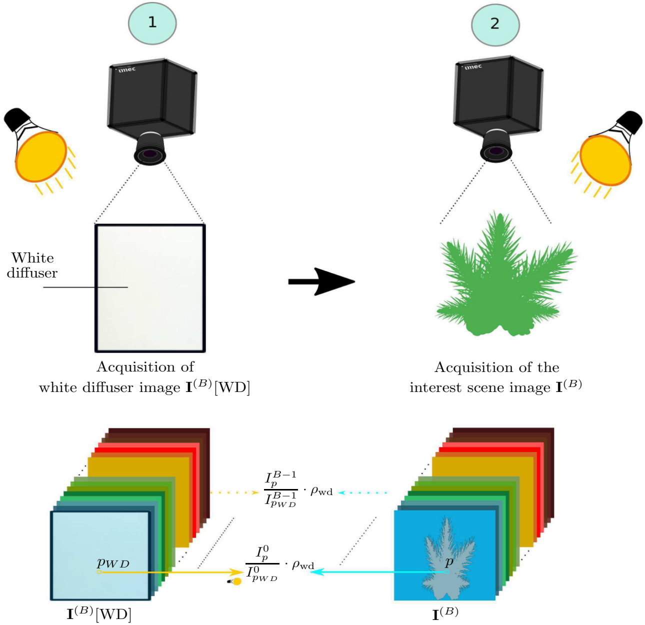


Acquisition of white diffuser image $\mathbf{I}^{(B)}[\mathrm{WD}]$

Acquisition of the interest scene image $\mathbf{I}^{(B)}$


1
2
White diffuser
Acquisition of white diffuser image $\mathbf{I}^{(B)}[\mathrm{WD}]$
Acquisition of the interest scene image $\mathbf{I}^{(B)}$
p_{WD}
$\frac{I_p^0}{I_{p_{WD}}^0} \cdot \rho_{\mathrm{wd}}$
p
$\mathbf{I}^{(B)}[\mathrm{WD}]$
$\mathbf{I}^{(B)}$


1
2
White diffuser
Acquisition of white diffuser image $\mathbf{I}^{(B)}[\mathrm{WD}]$
Acquisition of the interest scene image $\mathbf{I}^{(B)}$
$\frac{I_p^{B-1}}{I_{p_{WD}}^{B-1}} \cdot \rho_{\mathrm{wd}}$
p_{WD}
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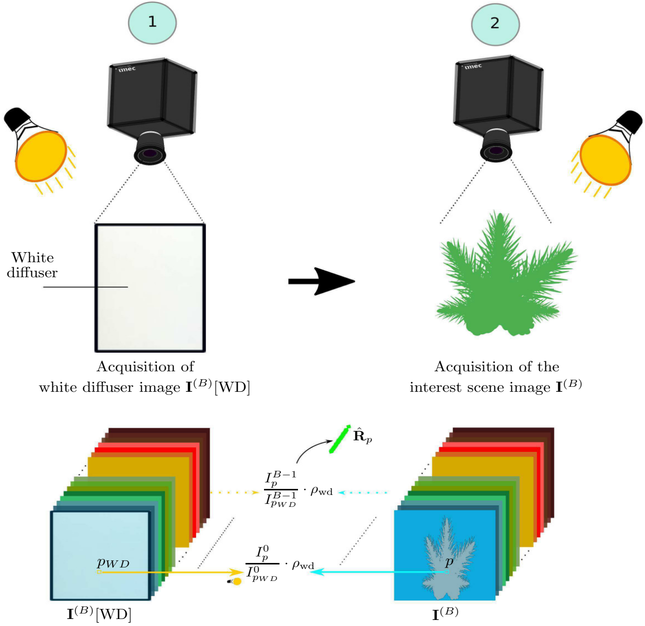
$\mathbf{I}^{(B)}$


1
2
imec
imec
White diffuser
Acquisition of white diffuser image $\mathbf{I}^{(B)}[\mathrm{WD}]$
Acquisition of the interest scene image $\mathbf{I}^{(B)}$
$\hat{\mathbf{R}}_p$
$\frac{I_p^{B-1}}{I_{p_{WD}}^{B-1}} \cdot \rho_{\mathrm{wd}}$
p_{WD}
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p
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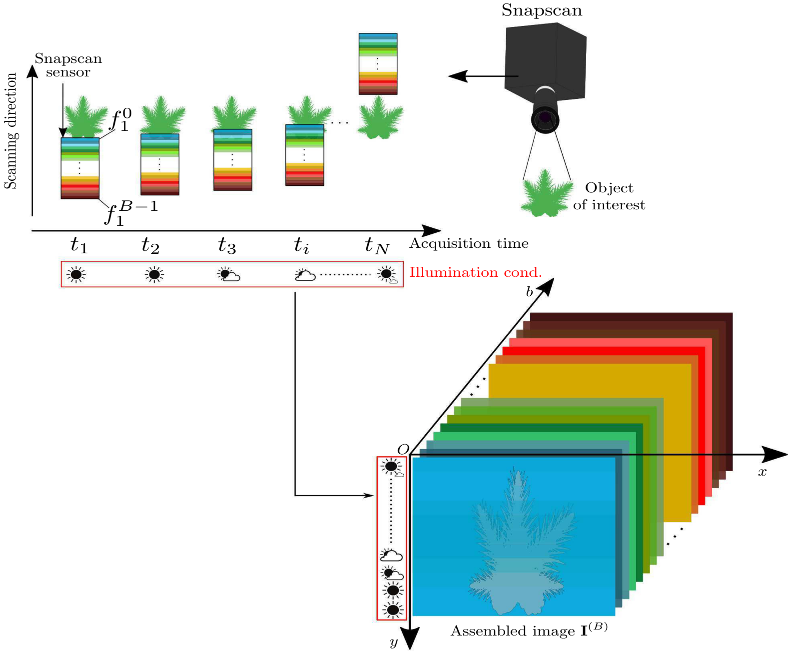
Frame acquisition and radiance image assembly



- Illumination (depends on both channel and pixel)
- Reflectance (to be estimated)

Multispectral image formation model[1]

$$I_p^b = Q\left(\tau \int_\Omega E_{t_p^b}(\lambda) \cdot R_p(\lambda) \cdot A_p(\lambda) \cdot T^b(\lambda)\ d\lambda\right) \quad (1)$$

- Optical attenuation (can be characterized)
- SSF of the b-th filter (known)

Assumptions for reflectance estimation

(i) Snapscan optical filters have ideal SSFs (Dirac delta functions).

[1] A. Amziane *et al.*, Reflectance estimation from multispectral linescan acquisitions under varying illumination–Application to outdoor weed identification, Sensors, 2021

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Assumptions for reflectance estimation

(i) Snapscan optical filters have ideal SSFs (Dirac delta functions).

(ii) Illumination is spatially uniform for each pixel row.

[1] A. Amziane *et al.*, Reflectance estimation from multispectral linescan acquisitions under varying illumination–Application to outdoor weed identification, Sensors, 2021

Assumption validation

Assumptions for reflectance estimation

✓(i) Snapscan narrowband filters approximate the Dirac delta assumption at best for today's technology

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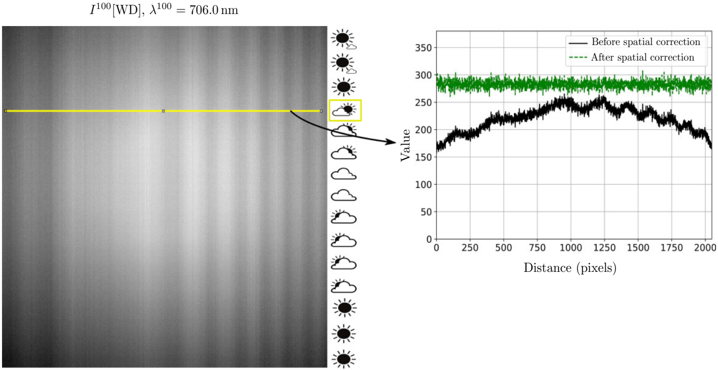
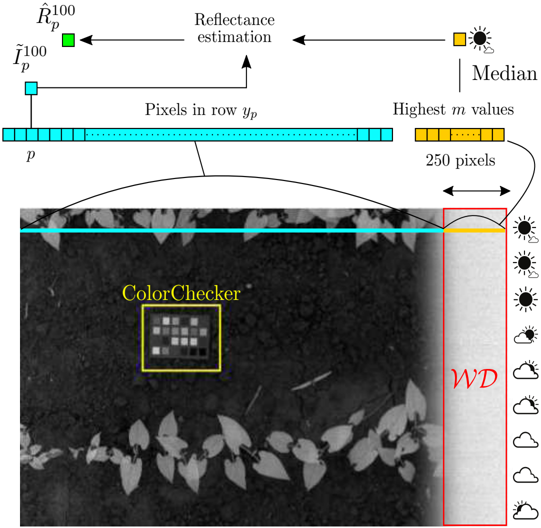
✓(ii) Spatial non-uniformity of illumination is compensated by vignetting correction



Row-wise (rw) method



Upper extract from channel $\tilde{I}^{100}$

[1] A. Amziane *et al.*, Frame-based reflectance estimation from multispectral images for weed identification in varying illumination conditions, International Conference on Image Processing Theory, Tools and Applications (IPTA), 2020.

Multispectral database: CA80

- 109 multispectral images ($\sim$349 GB)

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Mean absolute error (MAE) and Angular error ($\Delta\theta$)

Method	Illumination-based				Training-based
	rw (ours)	**wa**[1]	**ms**[2]	**dwd**[3]	**wn**[4]
MAE (%)	4.315	5.883	14.670	**3.236**	*3.628*
$\Delta\theta$ (rad)	**0.046**	**0.046**	0.309	*0.063*	*0.063*

Bold and italicized values show the best and second best performance respectively.

[1] F. Feyaerts *et al.*, Multi-spectral vision system for weed detection, Pattern Recognition Letters, 2001.

[2] H.A. Khan *et al.*, Illuminant estimation in multispectral imaging, Journal of the Optical Society of America A, 2017.

[3] J. Eckhard *et al.*, Outdoor scene reflectance measurements using a Bragg-grating-based hyperspectral imager, Applied Optics, 2015.

[4] P. Stigell *et al.*, Wiener estimation method in estimating of spectral reflectance from RGB images, Pattern Recognition and Image Analysis, 2007.

Pixel classification results

- Tasks: beet/weed detection and beet/thistle/goosefoot identification (37 images)
- Learning samples: 400,000 pixels per class
- Test samples: ∼13 M pixels
- Classifier: Gradient Boosting Machine (LightGBM[1] version)

		Radiance Feature	Reflectance Features				
			Illumination-Based				Training-Based
			rw (ours)	wa	ms	dwd	wn
Accuracy (%)	beet/weed detection	77.0	**86.1**	*84.7*	81.8	83.4	71.0
	Beet/thistle/goosefoot identification	39.5	*49.7*	**50.3**	46.5	46.0	34.0

- rw-based method provides a good trade-off between estimated reflectance quality and discrimination power

[1] G. Ke *et al.*, LightGBM: A highly efficient gradient boosting decision tree, NIPS, 2017.

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Accuracy (%)	beet/weed detection	77.0	**86.1**	*84.7*	81.8	83.4	71.0
	Beet/thistle/goosefoot identification	39.5	*49.7*	**50.3**	46.5	46.0	34.0

- rw-based method provides a good trade-off between estimated reflectance quality and discrimination power

[1] G. Ke *et al.*, LightGBM: A highly efficient gradient boosting decision tree, NIPS, 2017.

Data: 96 images

- Crops: beet, wheat, and bean
- Weeds: thistle, goosefoot, and datura
- Classification problems: Beet vs. weeds, wheat vs. weeds, and bean vs. weeds
- Learning data: 300,000 pixels per class
- Test data:
  - → Beet vs. weeds: ∼20 M pixels
  - → Wheat vs. weeds: ∼15 M pixels
  - → Bean vs. weeds: ∼11 M pixels

		Weed detection		Weed identification	
Metric	Crop	$\hat{\mathbf{R}}_{\mathrm{rw}}$	$\bar{\mathbf{R}}_{\mathrm{rw}}$	$\hat{\mathbf{R}}_{\mathrm{rw}}$	$\bar{\mathbf{R}}_{\mathrm{rw}}$
$\overline{\mathrm{Accuracy}}(\%)$	Beet	*86.0*	**89.2**	*61.8*	**69.0**
	Wheat	*90.4*	**94.0**	*54.6*	**60.7**
	Bean	*72.4*	**73.2**	*49.8*	**55.4**

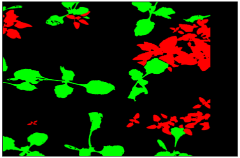
Unnormalized
Normalized

[1] A. Amziane *et al.*, Weed detection by analysis of multispectral images acquired under uncontrolled illumination conditions, International Conference on Quality Control by Artificial Vision (QCAV), 2021.

Test image 1

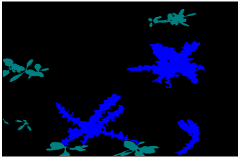
Test image 2

Crop Weed



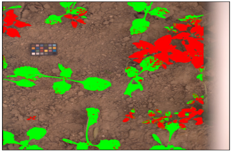
GT 1

Beet Thistle



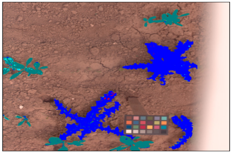
GT 2

92.5% 91.9%



($\overline{\mathrm{Acc.}}$=92.1%)

93.8% 97.8%

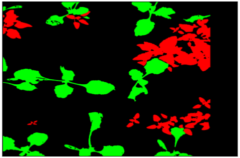
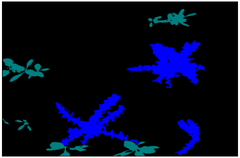
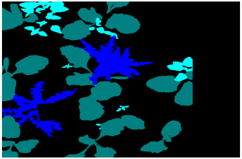


($\overline{\mathrm{Acc.}}$=95.0%)

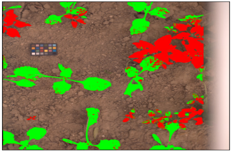
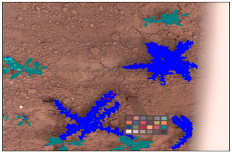
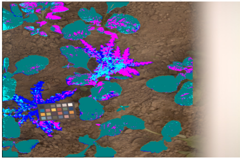
Test image 1 | Test image 2 | Test image 3

Crop Weed | Beet Thistle | Beet Thistle Goosefoot

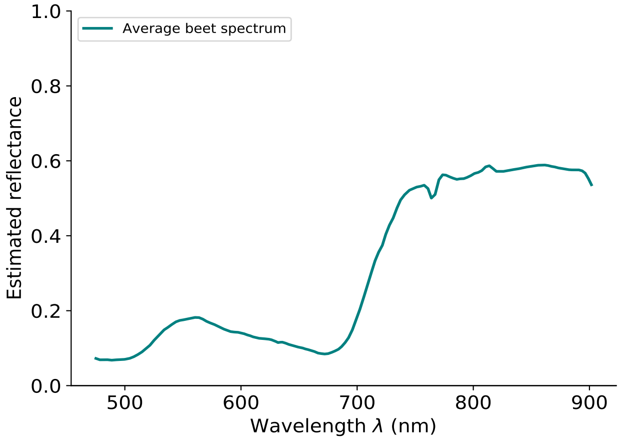
GT 1 | GT 2 | GT 3

92.5% 91.9% | 93.8% 97.8% | 86.8% 42.4% 8.2%

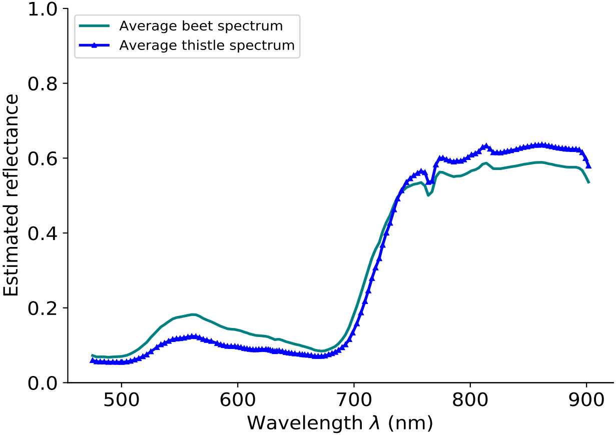
  

($\overline{\text{Acc.}}$=92.1%) | ($\overline{\text{Acc.}}$=95.0%) | ($\overline{\text{Acc.}}$=25.7%)

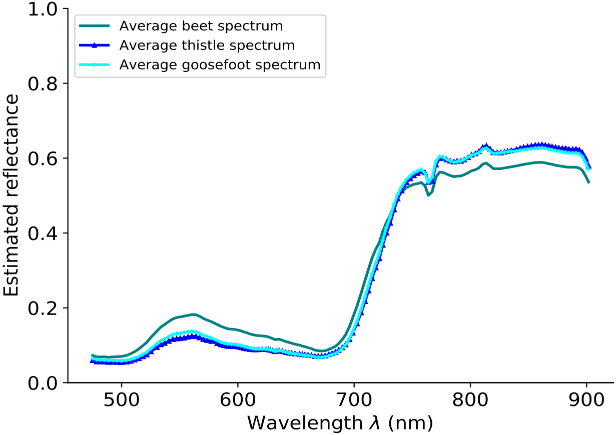
Spectral signatures are highly correlated



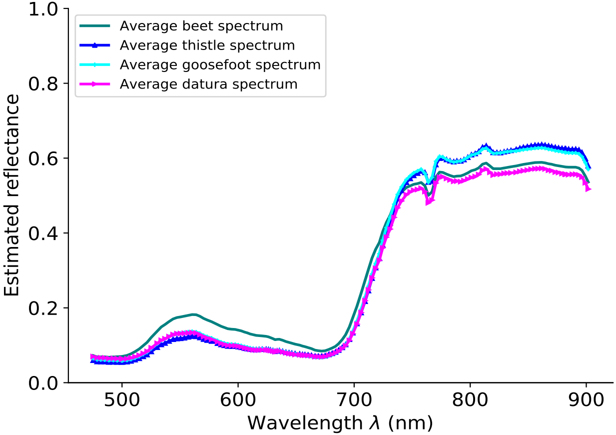
Spectral signatures are highly correlated



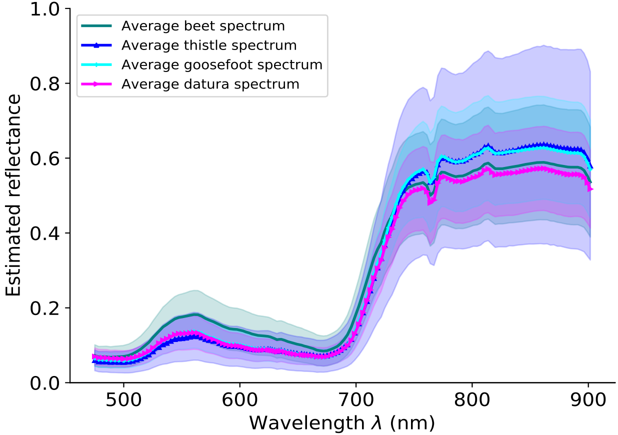
Spectral signatures are highly correlated



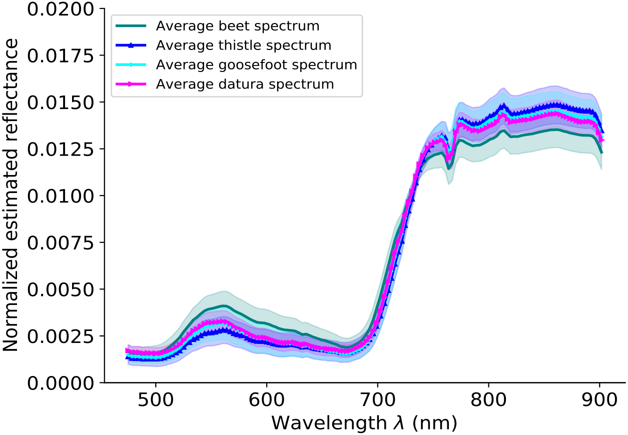
Spectral signatures are highly correlated



Spectral signatures are highly correlated



Spectral signatures are highly correlated



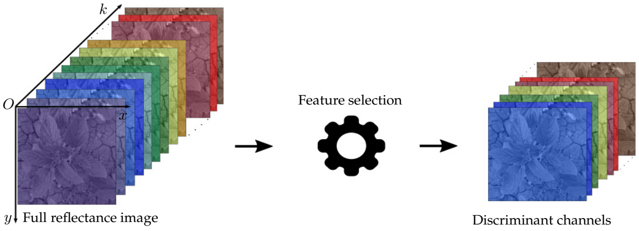
Overview

Problem

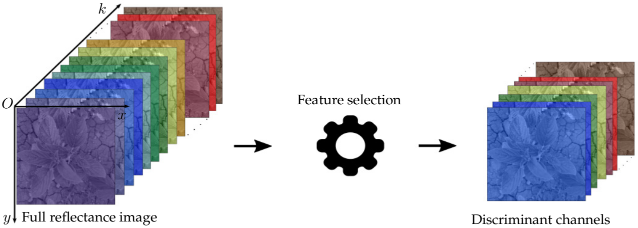
1. Computation greedy
2. May provide high-dimensional features
3. Difficult to consider spatio-spectral interactions efficiently

Proposed approach

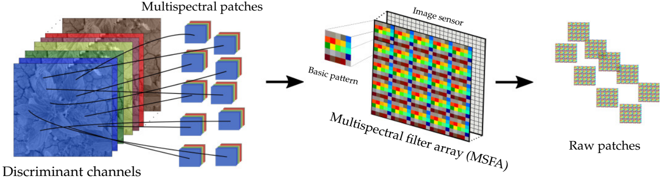
1 **Dimension reduction**



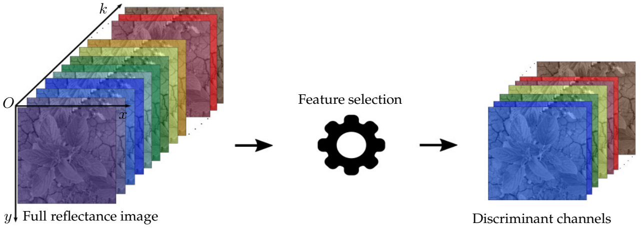
1 Dimension reduction



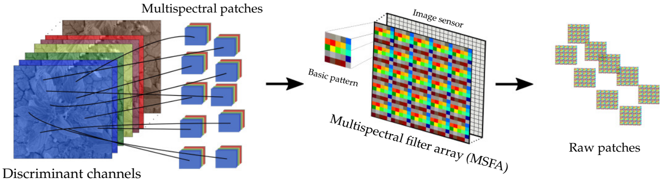
2 Raw patch simulation



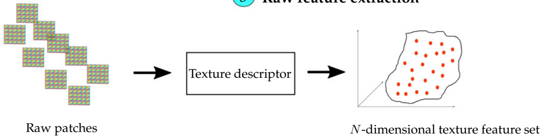
1 Dimension reduction



2 Raw patch simulation

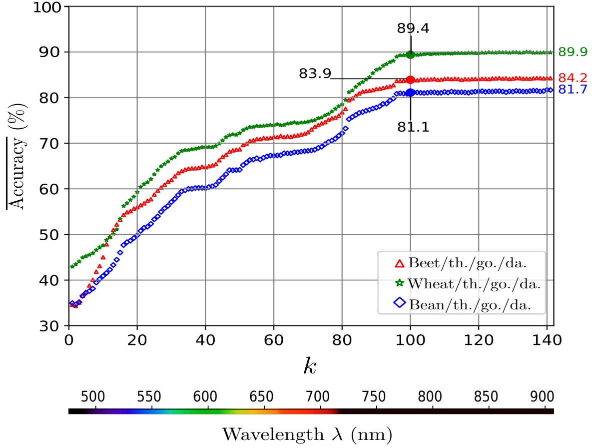


3 Raw feature extraction



Feature filtering

1. Filter out features that do not improve classifier performance



Feature filtering

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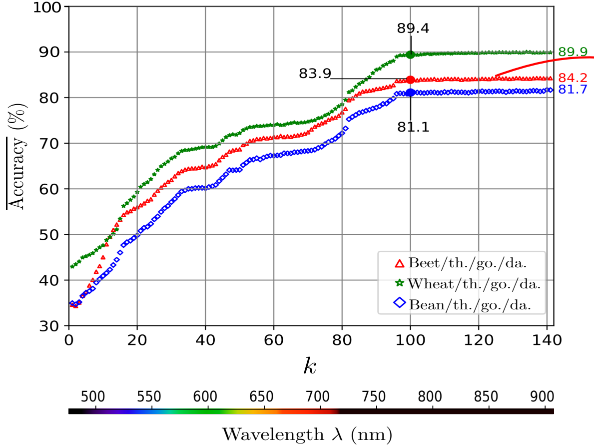
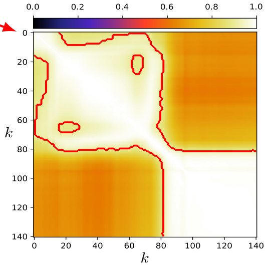
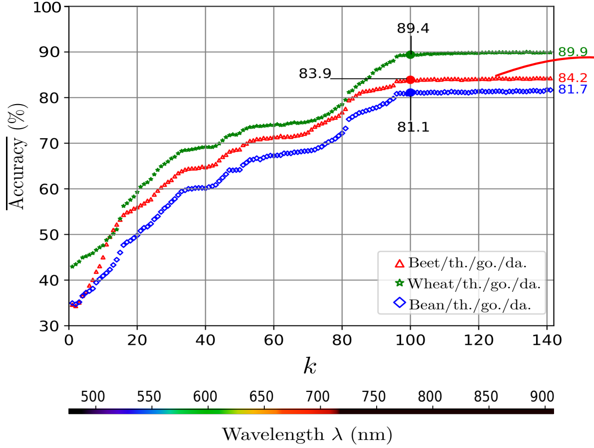


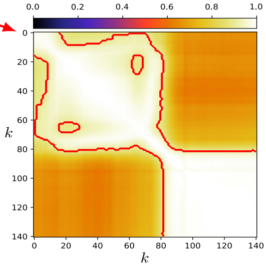


Pearson correlation values
of reflectance features associated
to beet/th./go./da. identification case

Feature filtering

1. Filter out features that do not improve classifier performance





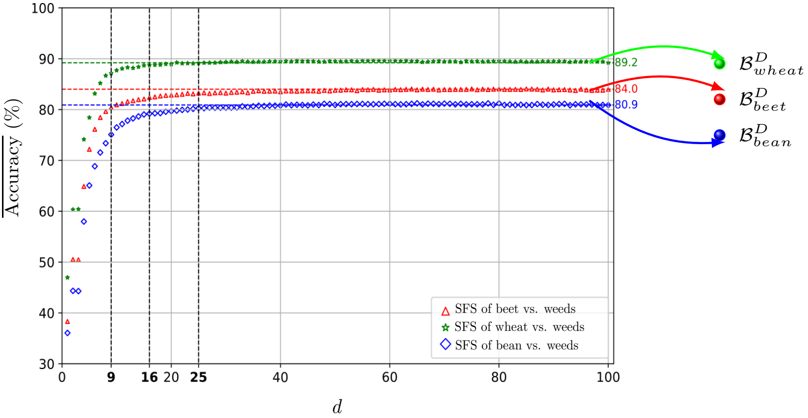
Pearson correlation values of reflectance features associated to beet/th./go./da. identification case

Result: A first reduced feature subset $\mathcal{B}^{K'}$, $K' = 100$

Sequential Forward Selection (SFS)

Problem-specific features

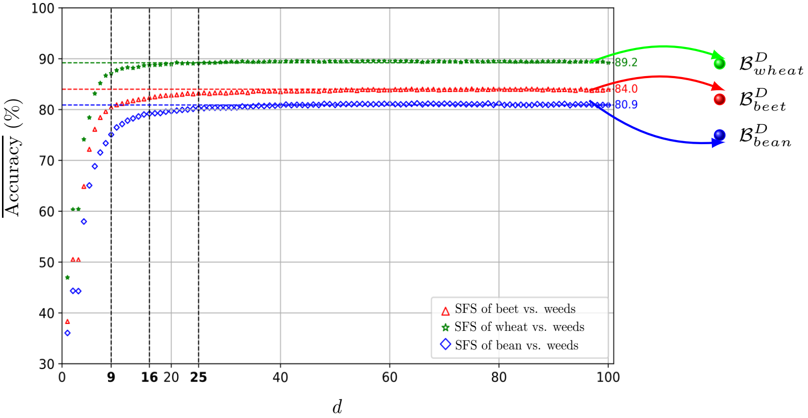
2. Select $D \in \{9, 16, 25\}$ discriminant features from the reduced subset $\mathcal{B}^{K'}$ using SFS method:



Sequential Forward Selection (SFS)

Problem-specific features

2. Select $D \in \{9, 16, 25\}$ discriminant features from the reduced subset $\mathcal{B}^{K'}$ using SFS method:



Global band selection

3. Use the problem-specific features and select those that are adapted to all problems

Global band validation

		Weed detection							
		Original features		Selected features					
Metric	Crop	$\hat{\mathbf{R}}_{\mathrm{rw}}$	$\bar{\mathbf{R}}_{\mathrm{rw}}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(25)}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(16)}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(9)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(25)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(16)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(9)}$
$\overline{\mathrm{Accuracy}}(\%)$	Beet	86.3	*89.2*	85.8	85.6	83.6	**89.3**	88.9	86.9
	Wheat	90.2	**94.1**	89.3	89.2	88.9	**94.1**	*93.9*	93.4
	Bean	*73.3*	**73.8**	71.7	70.5	69.0	69.7	68.0	65.8

		Weed identification							
		Original features		Selected features					
Crop	Metric	$\hat{\mathbf{R}}_{\mathrm{rw}}$	$\bar{\mathbf{R}}_{\mathrm{rw}}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(25)}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(16)}$	$\hat{\mathbf{R}}_{\mathrm{rw}}^{(9)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(25)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(16)}$	$\bar{\mathbf{R}}_{\mathrm{rw}}^{(9)}$
$\overline{\mathrm{Accuracy}}(\%)$	Beet	59.3	**68.6**	59.3	58.7	57.5	*67.1*	66.5	64.8
	Wheat	52.9	**58.3**	52.0	52.4	51.0	55.8	*56.0*	53.5
	Bean	48.9	**54.4**	48.1	47.7	47.0	*51.8*	50.8	48.7

- Unnormalized
- Normalized

MSFA design

Global bands for 5×5 MSFA design

- Band arrangement inspired from IMEC snapshot cameras (NIR 5×5)

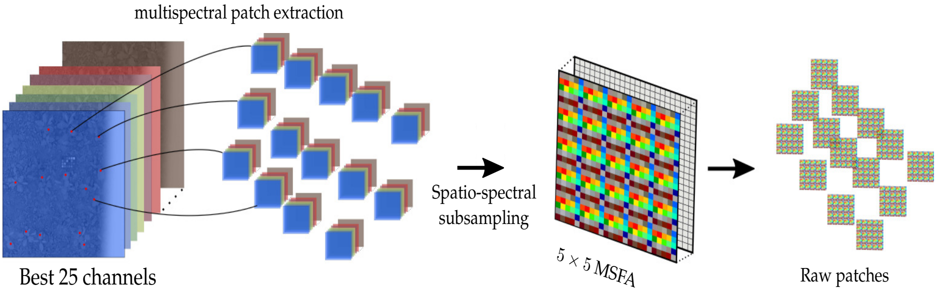
18	19	17	16	1	18	19	17	16	1	…
10	11	9	8	2	10	11	9	8	2	…
6	7	5	4	3	6	7	5	4	3	…
22	23	21	20	0	22	23	21	20	0	…
14	15	13	12	24	14	15	13	12	24	…
18	19	17	16	1	18	19	17	16	1	…
10	11	9	8	2	10	11	9	8	2	…
6	7	5	4	3	6	7	5	4	3	…
22	23	21	20	0	22	23	21	20	0	…
14	15	13	12	24	14	15	13	12	24	…
…	…	…	…	…	…	…	…	…	…	…

(a) Raw image ($D = 25$)

734.4	737.4	731.0	718.5	485.1
627.9	669.1	624.2	607.9	492.5
560.4	605.5	553.7	530.3	525.2
767.1	776.4	763.9	761.0	481.7
712.3	715.4	698.8	672.0	779.6

(b) Square basic pattern with no redundant band λ^d (nm), $d \in [\![0, 24]\!]$

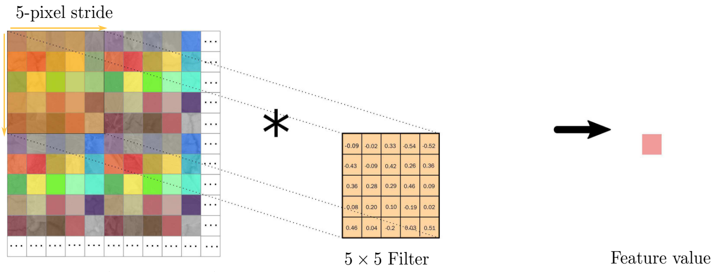
5×5 MSFA raw patch simulation



Raw texture feature extraction

Our proposition

Use convolutional filters that match the basic MSFA pattern to capture spatio-spectral interactions



Raw patch (25 × 25 pixels) simulated by 5 × 5 MSFA

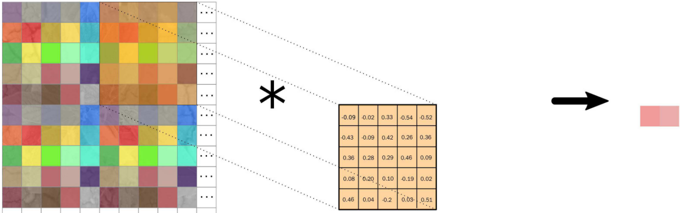
5 × 5 Filter

Feature value

Raw texture feature extraction

Our proposition

Use convolutional filters that match the basic MSFA pattern to capture spatio-spectral interactions



Raw patch (25×25 pixels) simulated by 5×5 MSFA

5×5 Filter

Feature values

Raw texture feature extraction

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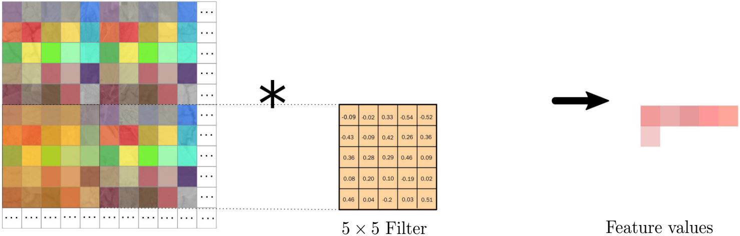


Raw patch (25×25 pixels) simulated by 5×5 MSFA

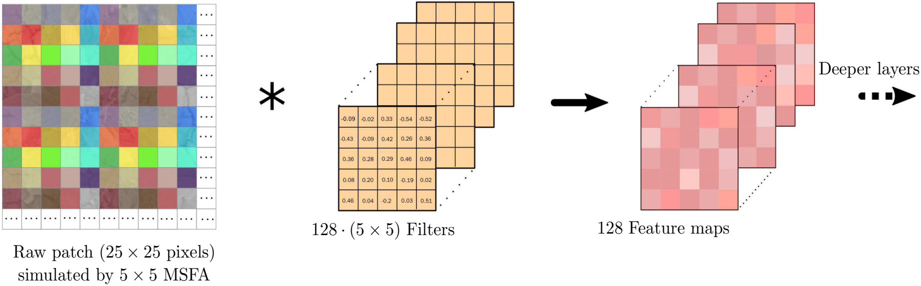
5×5 Filter

Feature values

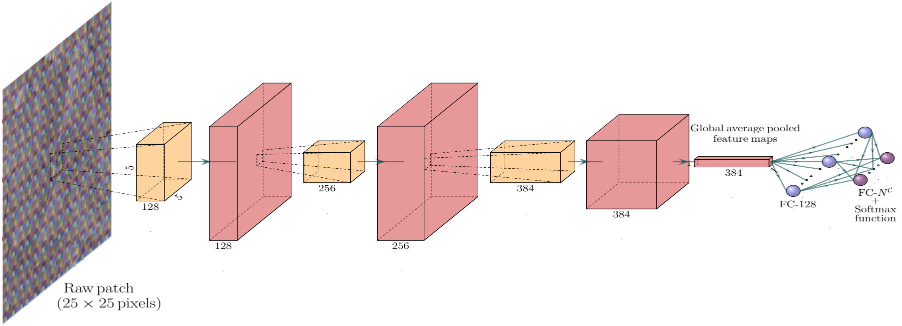
Raw texture feature extraction

Our proposition

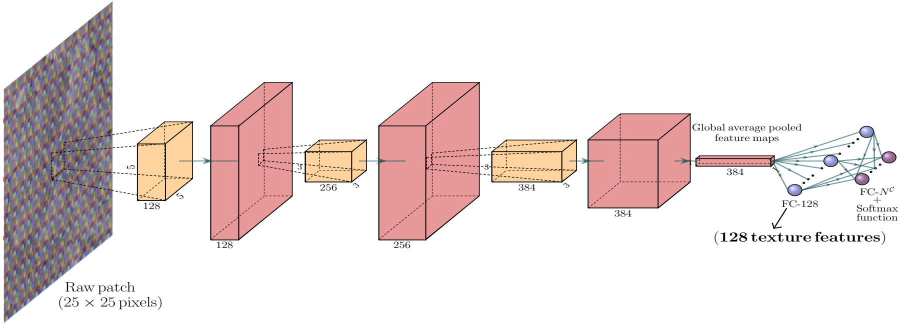
Use convolutional filters that match the basic MSFA pattern to capture spatio-spectral interactions

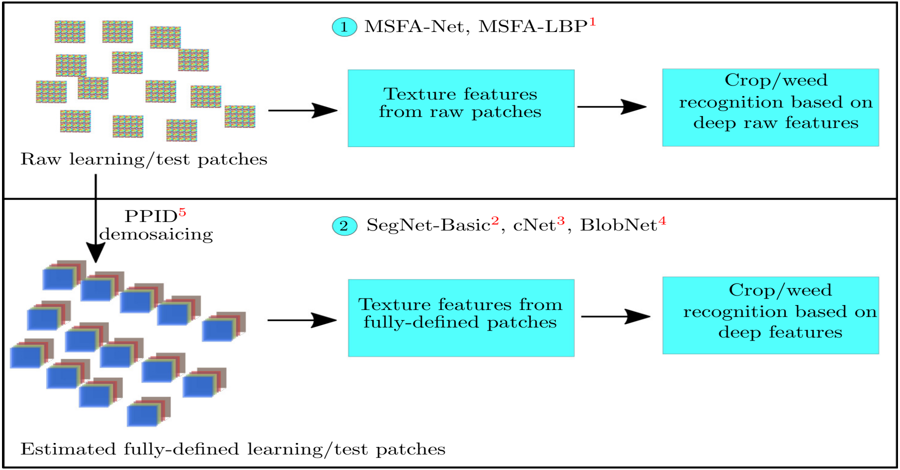


MSFA-Net: A CNN for raw texture feature extraction



MSFA-Net: A CNN for raw texture feature extraction





[1] S. Mihoubi *et al.*, Spatio-spectral binary patterns based on multispectral filter arrays for texture classification, JOSA A, 2018.

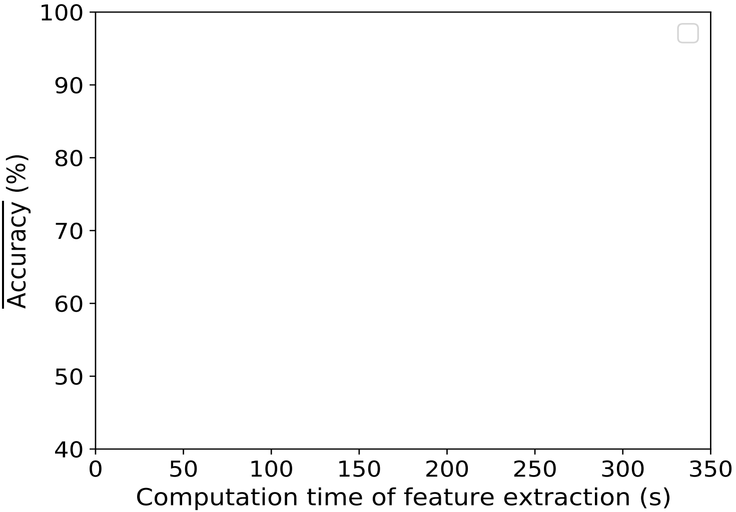
[2] V. Badrinarayanan *et al.*, SegNet: A deep convolutional encoder-decoder architecture for image segmentation, TPAMI, 2017.

[3] C. Potena *et al.*, Fast and accurate crop and weed identification with summarized train sets for precision agriculture, in Proceedings of IAS 2016.

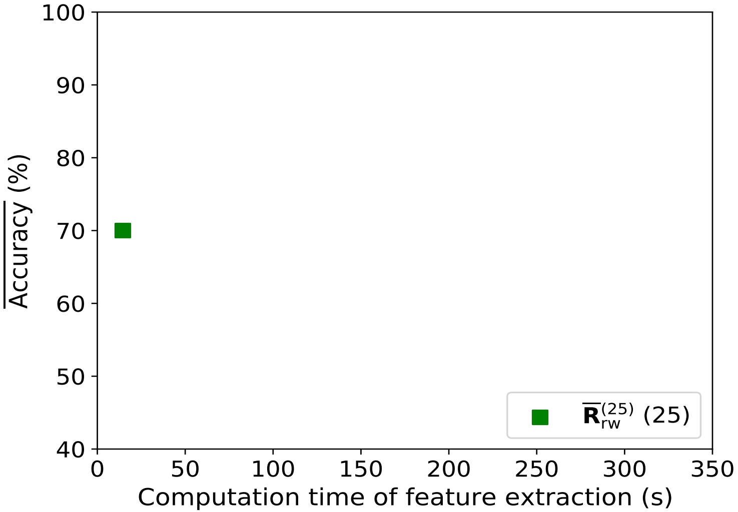
[4] A. Milioto *et al.*, Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs, in Proceedings of ICRA 2018.

[5] S. Mihoubi *et al.*, Multispectral demosaicing using pseudo-panchromatic image, IEEE TCI, 2017.

Accuracy vs. computation time

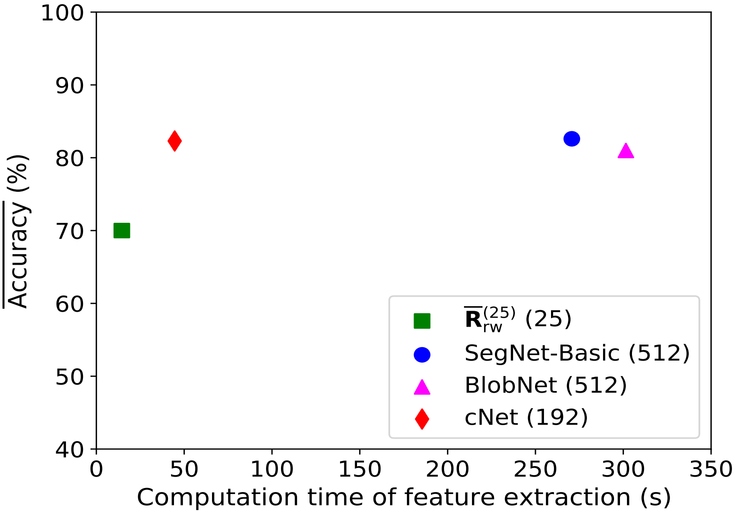


Accuracy vs. computation time



Bean/weed detection case

Accuracy vs. computation time



Bean/weed detection case

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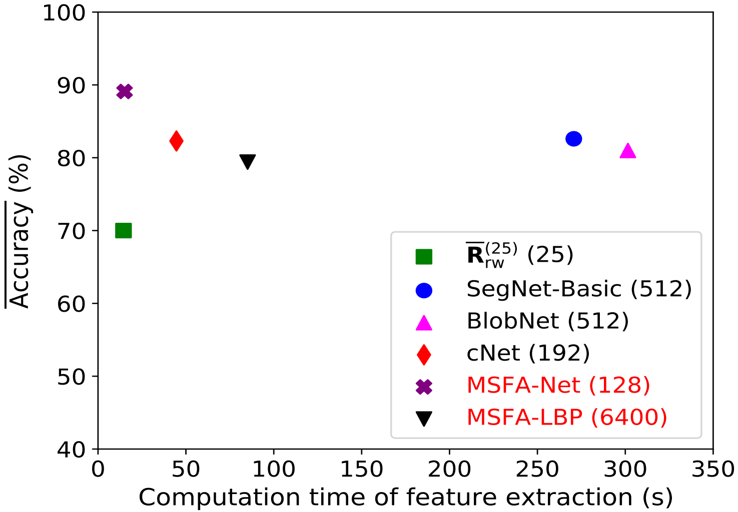
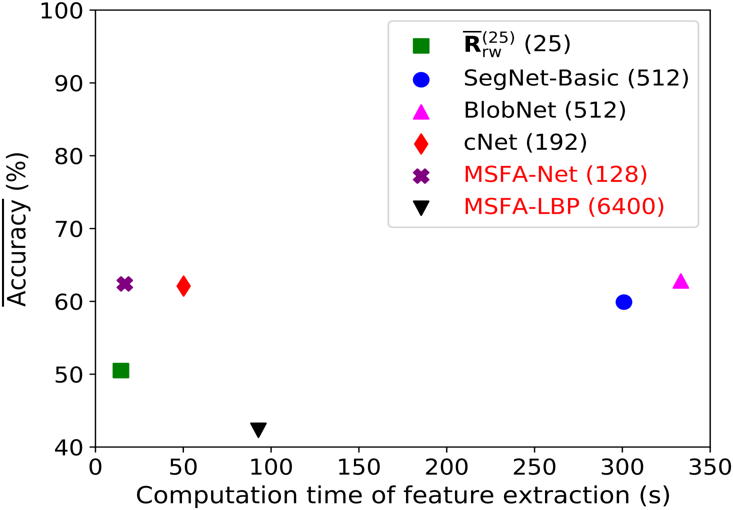


Bean/weed detection case

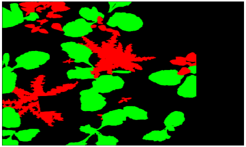
Accuracy vs. computation time



Bean/weed identification case

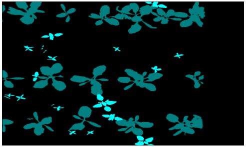
Segmentation results

Crop Weed



(a) GT1

Beet Goosefoot



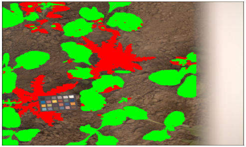
(b) GT2

Bean Datura

(c) GT3

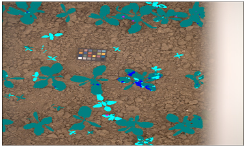
MSFA-Net (d–f)

96.7% *87.4%*



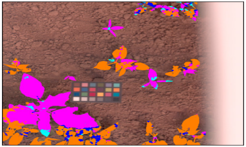
(d) ($\overline{\text{Acc.}}$=**90.4%**)

96.7% **75.2%**



(e) ($\overline{\text{Acc.}}$=**77.7%**)

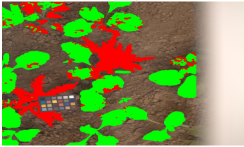
77.0% **89.9%**



(f) ($\overline{\text{Acc.}}$=**84.4%**)

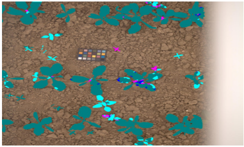
SegNet-Basic (i–k)

93.9% **87.9%**



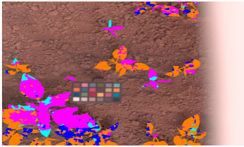
(i) ($\overline{\text{Acc.}}$=*89.9%*)

95.7% 58.0%



(j) ($\overline{\text{Acc.}}$=62.5%)

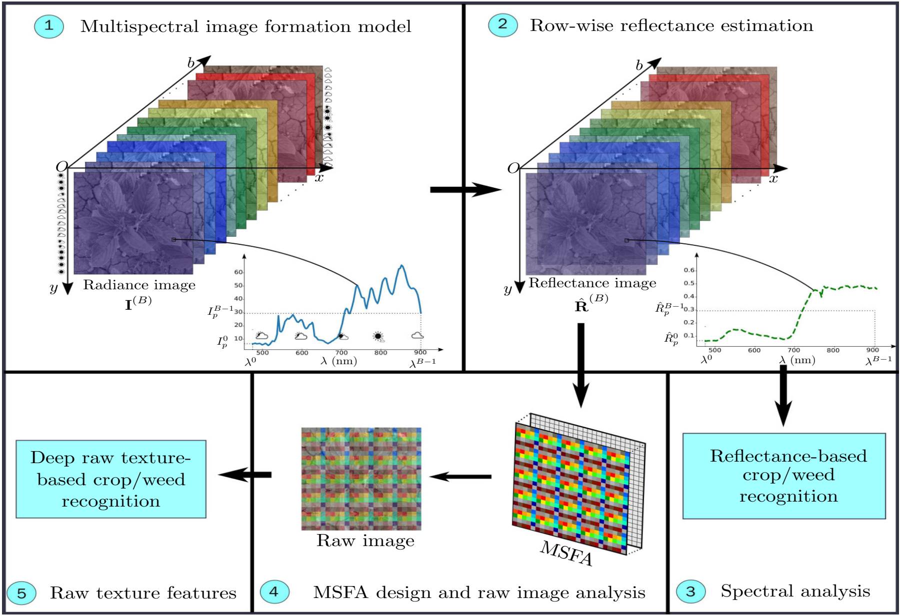
67.3% 77.2%



(k) ($\overline{\text{Acc.}}$=73.0%)

Overview

Conclusion



1 Multispectral image formation model
Radiance image $\mathbf{I}^{(B)}$
I_p^{B-1}
I_p^0
λ^0
λ (nm)
λ^{B-1}
2 Row-wise reflectance estimation
Reflectance image $\hat{\mathbf{R}}^{(B)}$
$\hat{R}_p^{B-1}$
$\hat{R}_p^0$
3 Spectral analysis
Reflectance-based crop/weed recognition
4 MSFA design and raw image analysis
MSFA
Raw image
5 Raw texture features
Deep raw texture-based crop/weed recognition

Perspectives

[1] V. Kitanovski *et al.*, Reflectance estimation from snapshot multispectral images captured under unknown illumination, in Proceedings of CIC 2021.

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1. Outdoor reflectance estimation from multispectral images without no reference device

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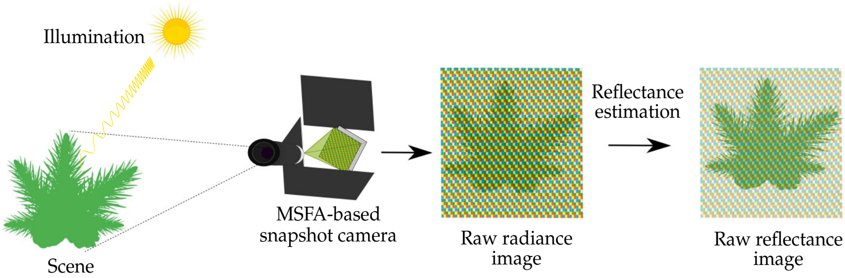
1. Outdoor reflectance estimation from multispectral images without no reference device
2. Reflectance estimation from raw images[1]:



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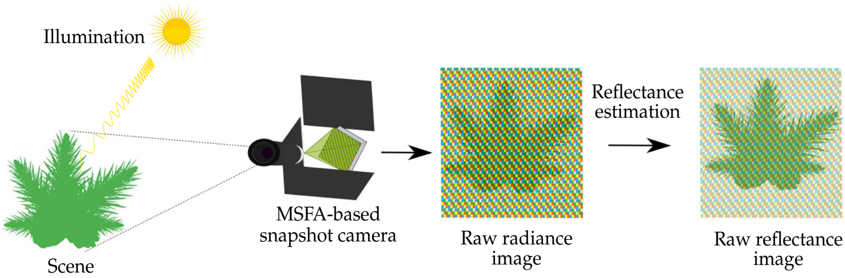

3. Combine reflectance spectra and deep learning-based texture features

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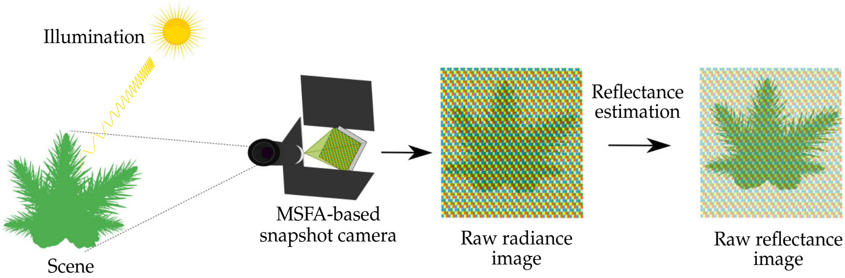
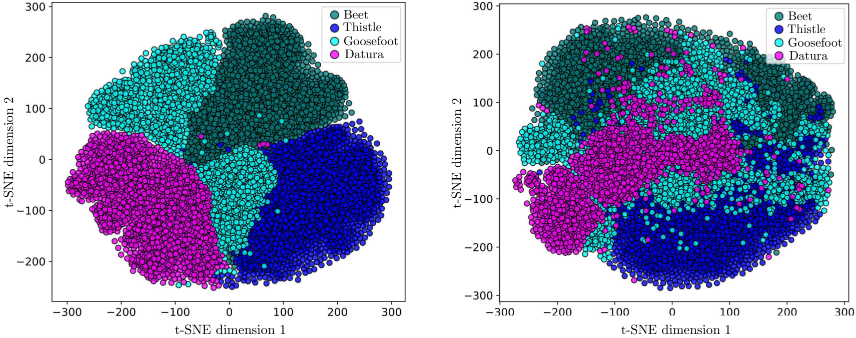


3. Combine reflectance spectra and deep learning-based texture features
4. Hierarchical crop/weed recognition

[1] V. Kitanovski *et al.*, Reflectance estimation from snapshot multispectral images captured under unknown illumination, in Proceedings of CIC 2021.

5. Domain adaptation:



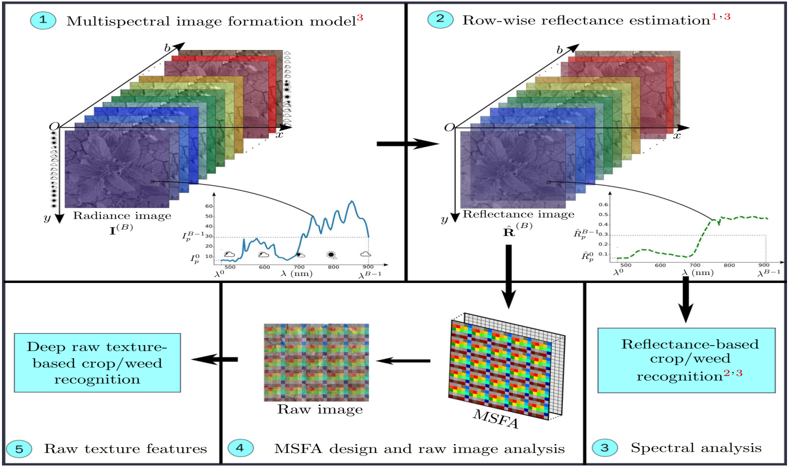
(a) Learning patches

(b) Test patches

t-SNE visualization of beet, thistle, goosefoot, and datura learning (a) and test (b) patches (2000/class), characterized by MSFA-Net.

[1] P. Lottes *et al.*, Unsupervised domain adaptation for transferring plant classification systems to new field environments, crops, and robots, in Proceedings of IROS 2020.

Thank you for your attention



[1] A. Amziane, O. Losson, B. Mathon, A. Dumenil, and L. macaire, "Frame-based reflectance estimation from multispectral images for weed identification in varying illumination conditions", In Proceedings of the 2020 Tenth International Conference on Image Processing Theory, Tools and Applications (IPTA), Paris, November 2020.

[2] A. Amziane, O. Losson, B. Mathon, L. macaire, and A. Dumenil, "Weed detection by analysis of multispectral images acquired under uncontrolled illumination conditions," in Fifteenth International Conference on Quality Control by Artificial Vision (QCAV), vol. 11794, Tokushima, Japan, May 2021.

[3] A. Amziane, O. Losson, B. Mathon, A. Dumenil, and L. macaire,"Reflectance estimation from multispectral linescan acquisitions under varying illumination–Application to outdoor weed identification," Sensors, vol. 21, no. 11, p. 3601, May 2021.