Using Spatial Correspondences for Hyperspectral Knowledge Transfer: Evaluation on Synthetic Data

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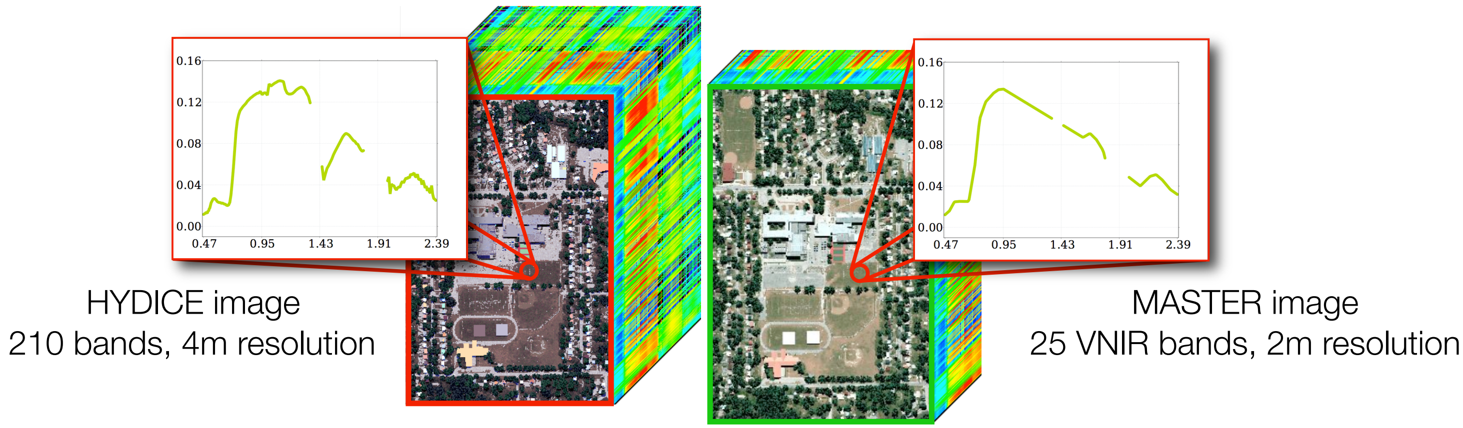
Class Knowledge Transfer Between Images

- Images with similar material distributions captured by different sensors can have differences in spatial and spectral resolution.



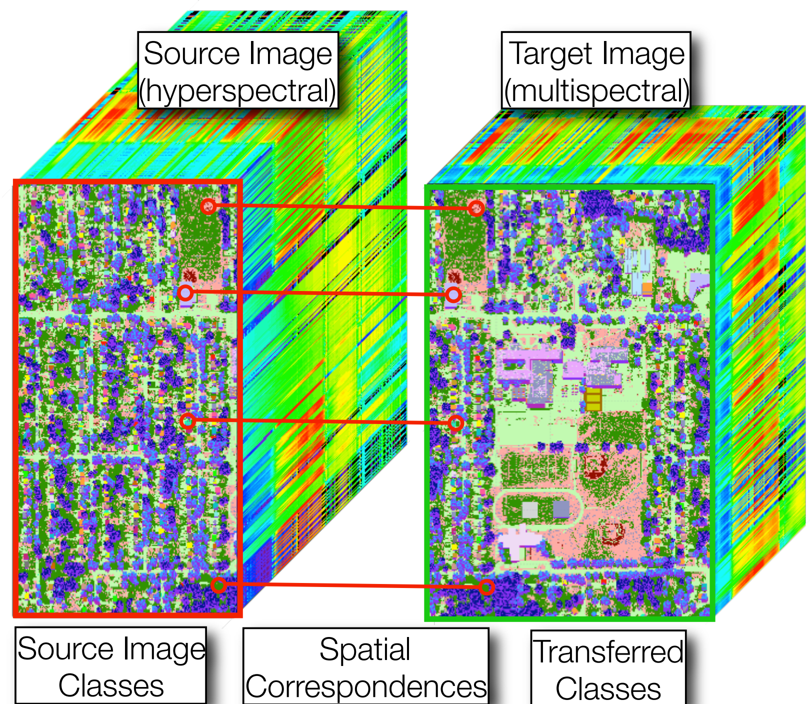
- Exploiting knowledge of class structure in one image can help label new imagery.
- Potential benefits:
  - Decreased labeling expense
  - Improved classification accuracy
  - Reduced computational burden
- Automatically transferring class knowledge between images is nontrivial
- Previous work demonstrated success in knowledge transfer between spatially and temporally related imagery. (Rajan et al. 2006)
- This work will focus on class knowledge transfer between images captured with different sensors

Class Knowledge Transfer Between Sensors

- **Scenario for this work:** exploit knowledge of *class structure* in a "source" image, captured with a ***hyperspectral*** sensor, to transfer known classes to a "target" image captured using a ***multispectral*** sensor.

Our approach:

- characterize the partitions produced by a classifier on the source image
- determine a set of (spatial) correspondences between the source and target image
- propagate source labels to target image according to relative class relationships *within* and *between* the images



Problem Statement and Assumptions

- Let $\mathbf{S}=[x^{\mathbf{S}}_{i,1}, \ldots, x^{\mathbf{S}}_{i,d}],\ i \in [1, n_{\mathbf{S}}],\ \mathbf{T}=[x^{\mathbf{T}}_{j,1}, \ldots, x^{\mathbf{T}}_{j,d}],\ j \in [1, n_{\mathbf{T}}]$ be the set of d-dimensional source and target image spectra, respectively.
  - Since $\mathbf{S}$ and $\mathbf{T}$ differ in spectral resolution, we upsample the lower resolution spectra to the higher resolution spectra.
- For each source spectrum, we have a corresponding label $y^{\mathbf{S}}_i \in [1, n^{\mathbf{S}}_{class}]$
- We wish to assign labels $y^{\mathbf{T}}_j \in [0,\ n^{\mathbf{S}}_{class}]$ to each target spectrum $\mathbf{x}^{\mathbf{T}}_j \in \mathbf{T}$, where $y^{\mathbf{T}}_j = 0$ indicates that $\mathbf{x}^{\mathbf{T}}_j$ does **not** belong to a known source class.

Assumptions:

I. Class distributions of $\mathbf{S}$ and $\mathbf{T}$ images “similar” (e.g., both are images of urban areas)

II. $n^{\mathbf{S}}_{class} \neq n^{\mathbf{T}}_{class}$ (the number of source and target classes are not necessarily equal)

III. Source and target spectra converted to reflectance via an appropriate atmospheric compensation technique

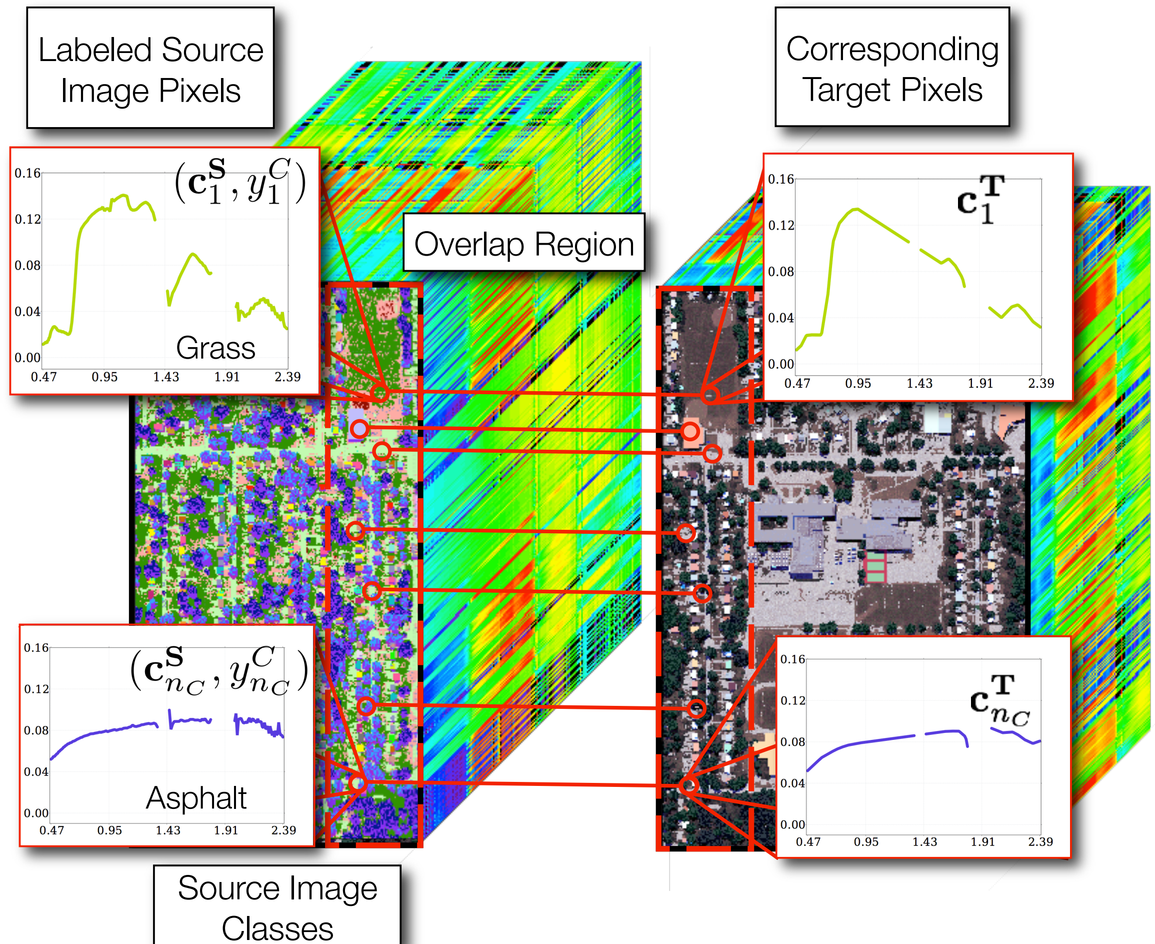
IV. Linear illumination effects eliminated
by scaling each spectrum by its Euclidean norm

Spatial Correspondence Points

- To map source image classes to the target image, we define a set of n_C *correspondence points*:

$$C = \{(\mathbf{c}_i^{\mathbf{S}}, \mathbf{c}_i^{\mathbf{T}}, y_i^C)\}_{i=1}^{n_C}$$

  where $\mathbf{c}_i^{\mathbf{S}}$ and $\mathbf{c}_i^{\mathbf{T}}$ are spatially corresponding spectra in the the source and target images, with source label y_i^C.
- We assume correspondence points exist for all source image classes



Capturing Interclass Relationships with Relation Vectors

- Given an input spectrum $\mathbf{x}$ and a set of k class mean vectors $\mathbf{M}=\{\mathbf{m}_1, \ldots, \mathbf{m}_k\}$, the *relation vector* between $\mathbf{x}$ and $\mathbf{M}$ is defined as:

$$\mathrm{rel}(\mathbf{x}, \mathbf{M}) = \left[\frac{\mathrm{d}(\mathbf{x}, \mathbf{m}_1)}{\sum_j^k \mathrm{d}(\mathbf{x}, \mathbf{m}_j)}, \ldots, \frac{\mathrm{d}(\mathbf{x}, \mathbf{m}_k)}{\sum_j^k \mathrm{d}(\mathbf{x}, \mathbf{m}_j)} \right]$$

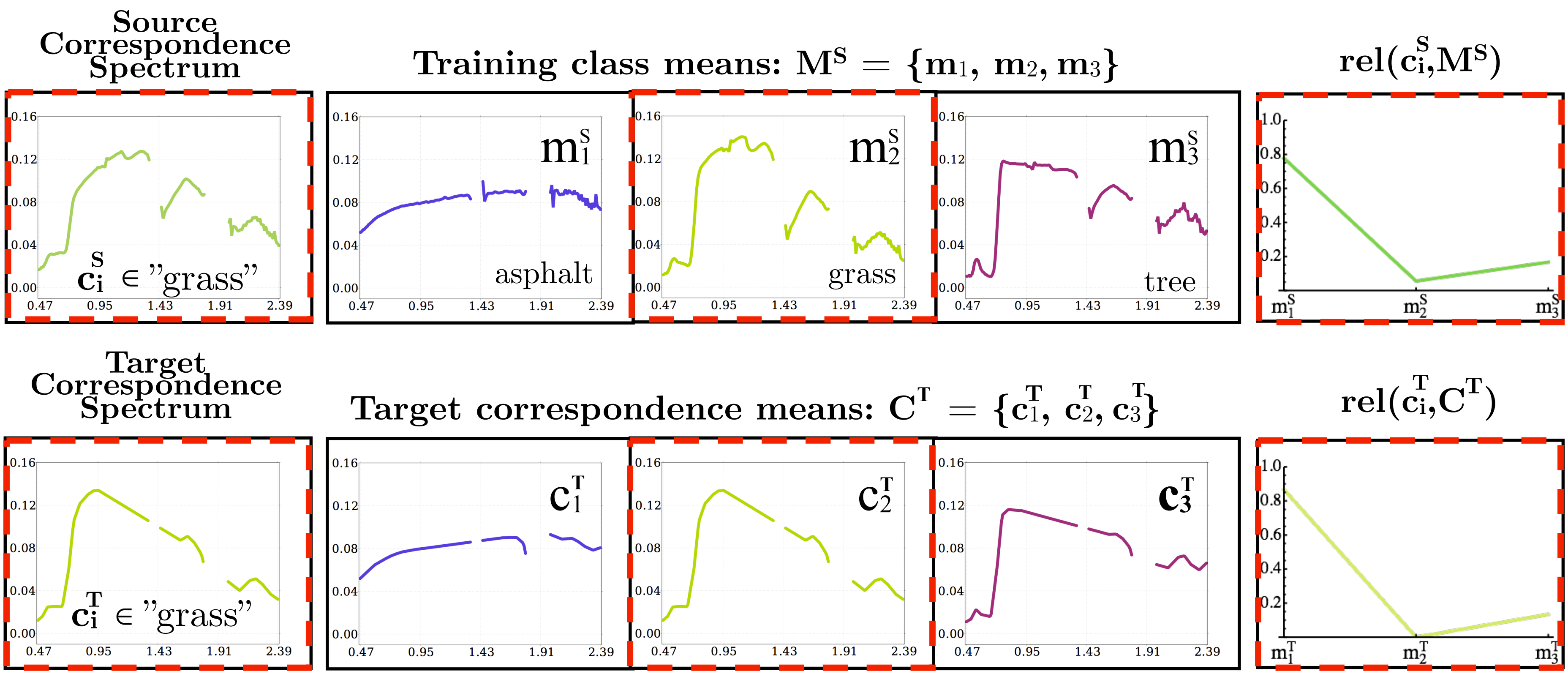
  where $\mathrm{d}(\mathbf{x}, \mathbf{m}) = \|\mathbf{x} - \mathbf{m}\|_2$.

- Each entry of the relation vector estimates the likelihood of distinguishing spectrum $\mathbf{x}$ from a particular class mean (Chang, 2000).
- We use the following function to compare a pair of relation vectors $\mathbf{r}_1$ and $\mathbf{r}_2$

$$\mathrm{relsim}(\mathbf{r}_1, \mathbf{r}_2) = 1 - \frac{1}{2}||\mathbf{r}_1 - \mathbf{r}_2||_2 \in [0, 1]$$

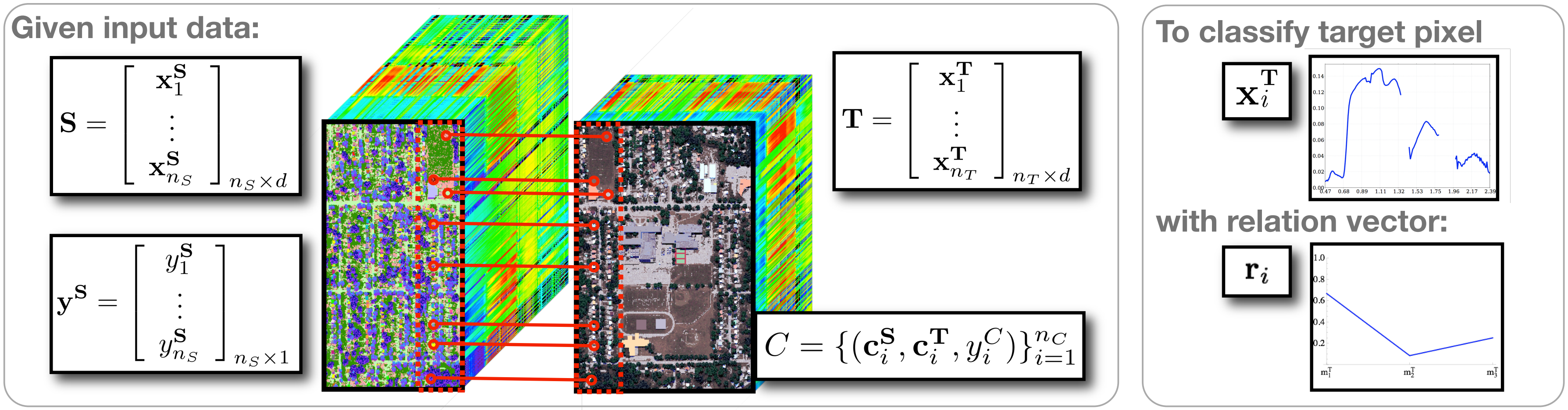
  which yields values approaching one if $\mathbf{r}_1$ and $\mathbf{r}_2$ are similar.

Capturing Interclass Relationships with Relation Vectors

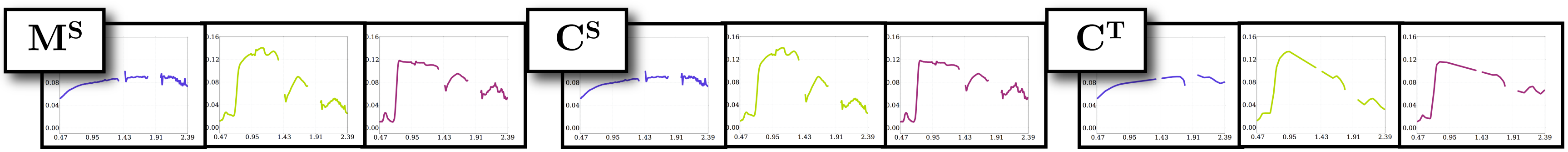


Observation: relative class relationships in source image are similarly related in the target image.

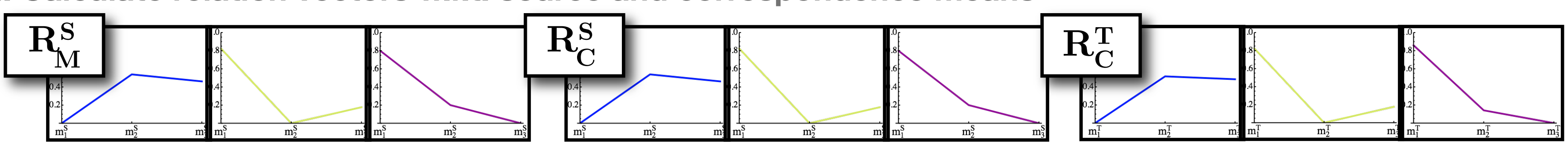
RelTrans Algorithm



I. Calculate mean vectors for source data and correspondence points



II. Calculate relation vectors w.r.t. source and correspondence means



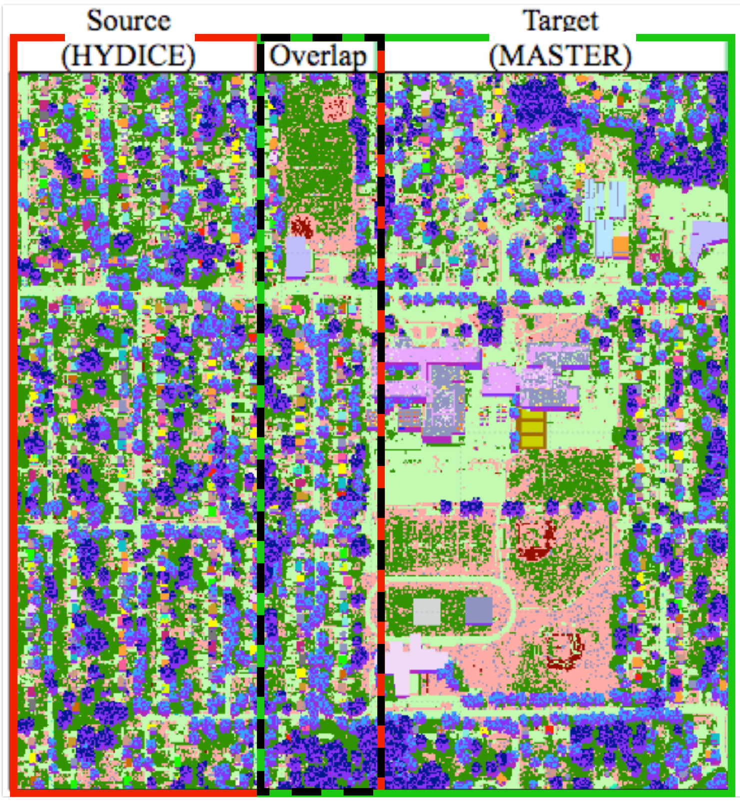
III. Form weighted similarity matrix between relation vector vs. training data and correspondences

$$\mathbf{W}(i,j) = \mathrm{relsim}(\mathbf{r}_i, \mathbf{R}_{\mathbf{M}}^{\mathbf{S}}) \cdot \mathrm{relsim}(\mathbf{r}_i, \mathbf{R}_{\mathbf{C}}^{\mathbf{S}}) \cdot \mathrm{relsim}(\mathbf{r}_i, \mathbf{R}_{\mathbf{C}}^{\mathbf{T}}) \ \forall j \in [1, n_{class}^{\mathbf{S}}]$$

IV. Predict label for target pixel

$$y_i^{\mathbf{T}} = \begin{cases} \underset{j}{\mathrm{argmax}}\ \mathbf{W}(i,j) & \text{if } \mathbf{W}(i,j) > \tau \\ 0 & \text{otherwise} \end{cases}$$

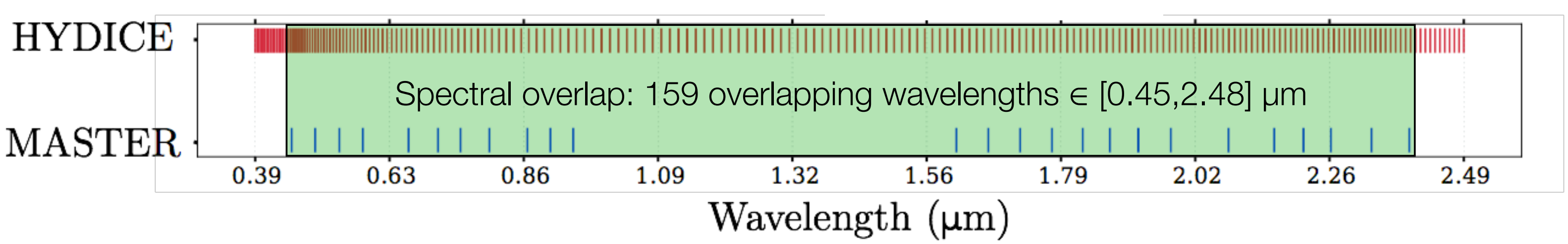
Source/Target Imagery and Image Classes



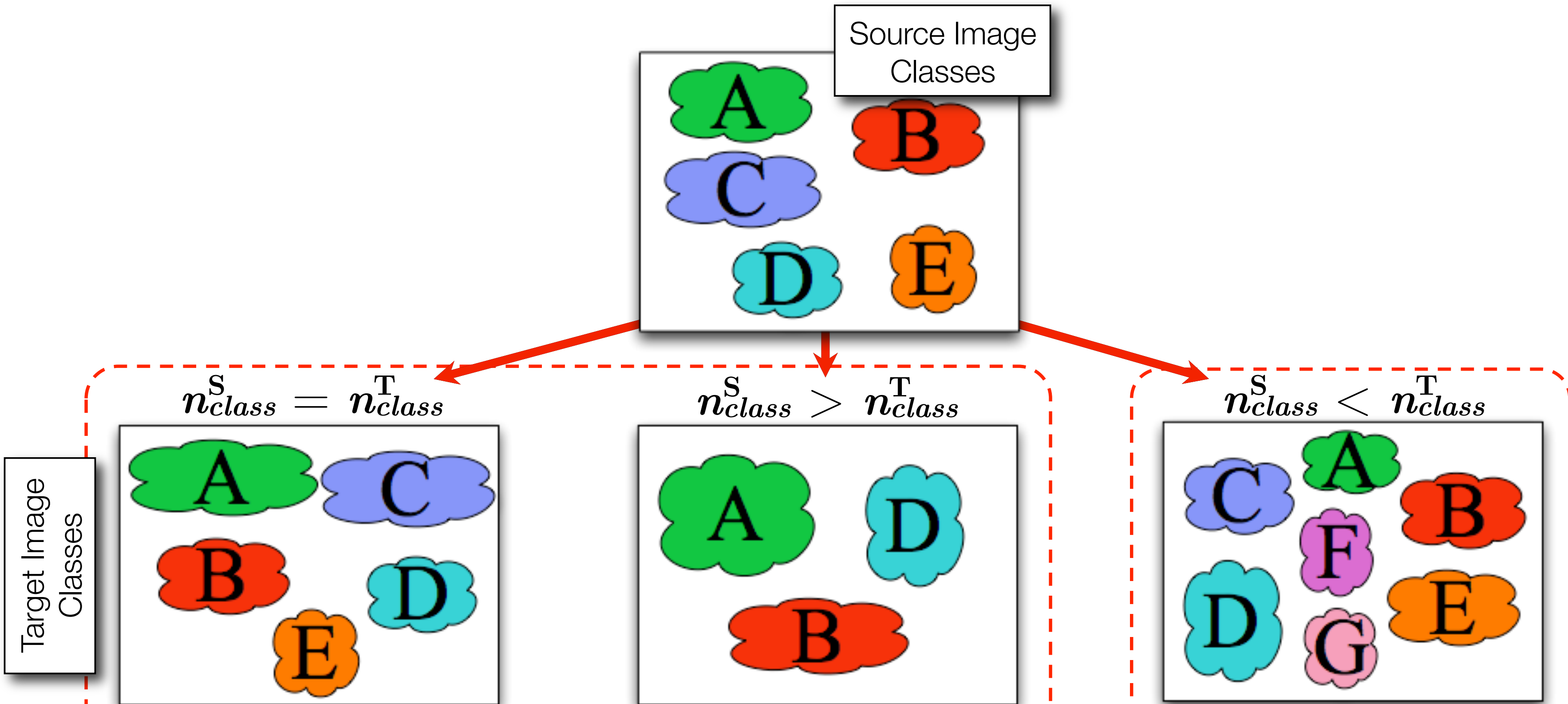
RIT DIRSIG Synthetic Imagery (Schott, 1999)
400x400 pixels
2m/pixel resolution
70 different surface materials

Source image (400 x 263)
  HYDICE wavelengths: 210 bands
Target image (400 x 202)
  MASTER wavelengths: 25 VNIR bands
Spatial overlap: 400 x 61 pixels
Spectral overlap: 159 wavelengths

Source Image Segmentation (Merényi et al., 2009)
  Spectra selected by stratified sampling
  $n_S = n_T = 2000$ source/target spectra sampled
  $n_C = 300$ correspondence points



Evaluation Scenarios for Knowledge Transfer



- One-to-one correspondence between number of classes in source and target images
- Source image contains classes not present in target image
- Target image contains classes missing from source image
- Class discovery possible

Knowledge Transfer Results on DIRSIG Synthetic Imagery

	Overall Accuracy		
	$n^{\mathrm{S}}_{class} = n^{\mathrm{T}}_{class}$	$n^{\mathrm{S}}_{class} > n^{\mathrm{T}}_{class}$	$n^{\mathrm{S}}_{class} < n^{\mathrm{T}}_{class}$
MinDist	0.858 (1.898e-03)	0.825 (4.922e-04)	0.579 (2.054e-04)
$\mathbf{MinDist}_{\mathrm{rel}}$	0.947 (3.355e-04)	0.877 (4.197e-04)	0.640 (1.038e-04)
$\mathbf{RelTrans}_{\mathrm{source}}$	0.947 (3.355e-04)	0.877 (4.197e-04)	0.640 (1.038e-04)
$\mathbf{RelTrans}_{\mathrm{corr}}$	0.990 (3.454e-06)	0.933 (1.736e-05)	0.664 (2.036e-06)
$\mathbf{RelTrans}_{\mathrm{thresh}}$	0.990 (3.454e-06)	0.933 (1.736e-05)	0.986 (7.458e-06)

Evaluation details:

- 10-fold cross validation (mean/variance provided above)
- 99% relsim threshold

MinDist vs. RelTrans Thresholding Accuracy

Intuition: a more robust descriptor imposes a superior sort order than a less robust descriptor in terms of similarity measurements.

Thus, if we threshold the same number of points for each classifier, the one utilizing the better descriptor will yield higher classification accuracy.

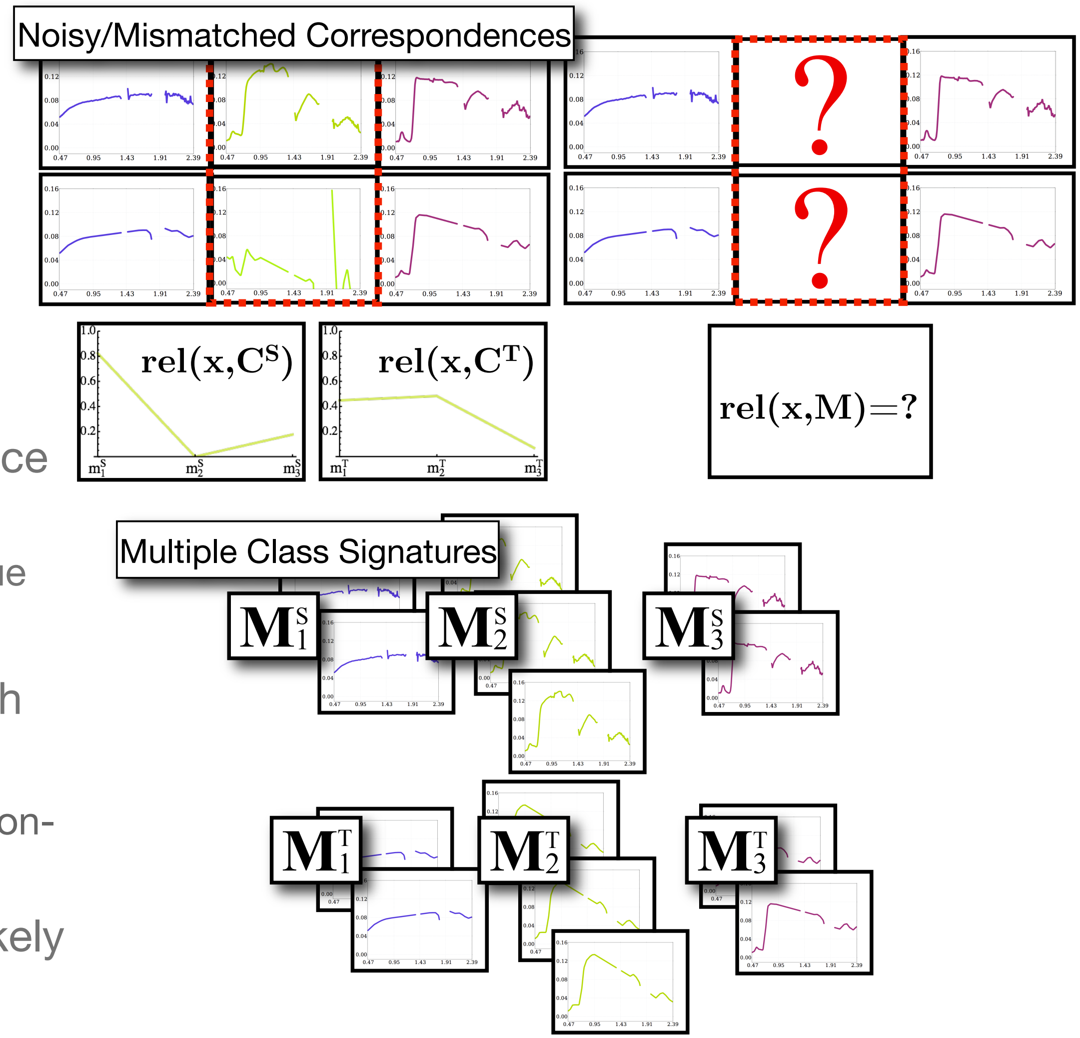
$\mathbf{RelTrans_{thresh}}$: marks relation vectors with relsim values less than τ as unknowns
$\mathbf{MinDist_{nthresh}}$: marks same number of pixels as $\mathbf{RelTrans_{thresh}}$ as unknowns

$n^{\mathbf{S}}_{class} < n^{\mathbf{T}}_{class}$

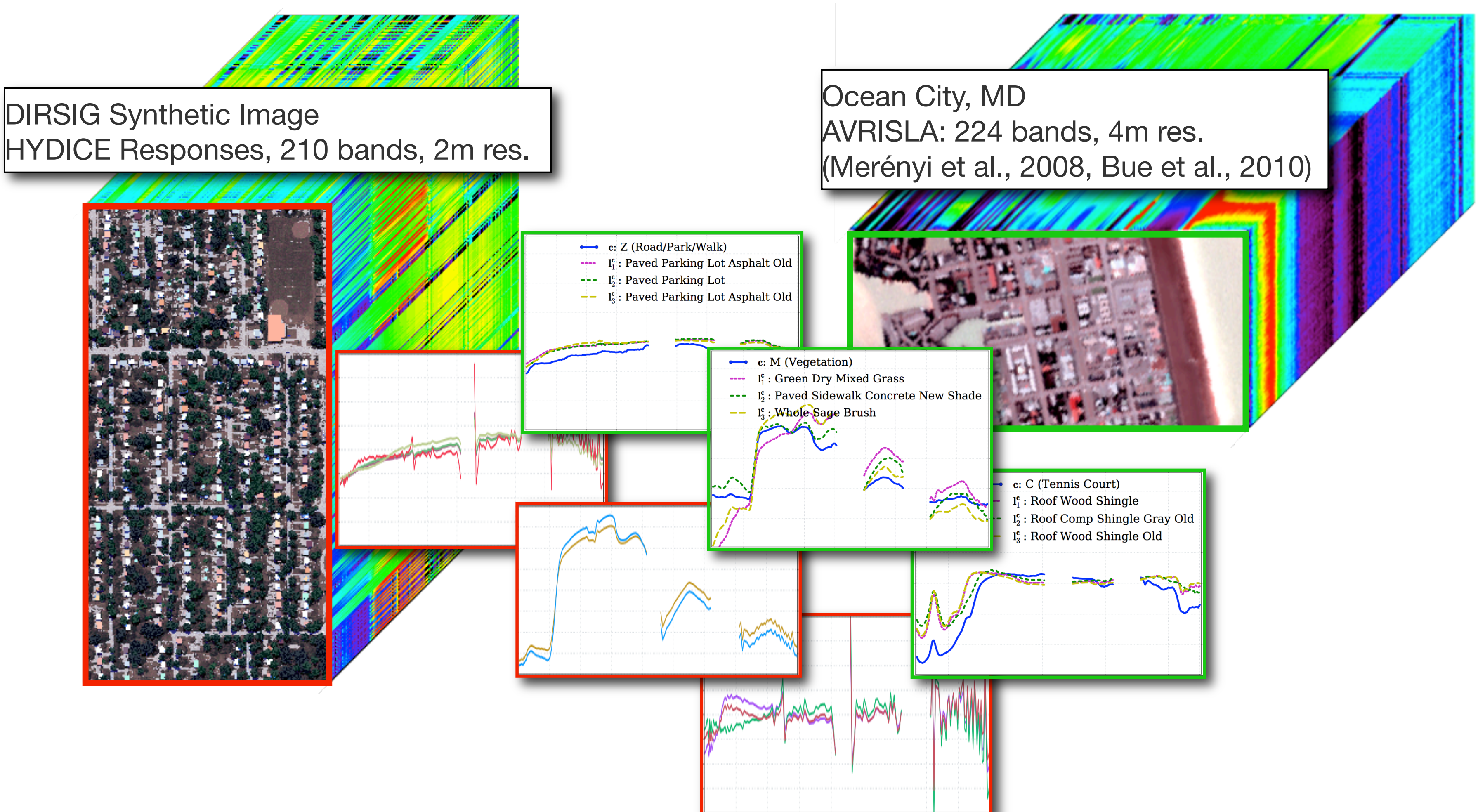
	$\tau = \mathbf{95\%}$	$\tau = \mathbf{97\%}$	$\tau = \mathbf{99\%}$
$\mathbf{RelTrans_{thresh}}$	**75.0**	**95.9**	**98.7**
$\mathbf{MinDist_{nthresh}}$	60.8	73.1	86.3

Limitations

- Dissimilar class relationships in source and target images will lead to poor transfer performance
  - Assess sensitivity to noise
- Mean vectors alone may not adequately capture class variance
  - Employing multiple class signatures may alleviate this issue
- Spatial overlap rarely occurs with multisensor data
  - Explore automatic detection of non-spatial correspondence points
- More sophisticated classifiers likely necessary for real data



Future work: Synthetic to Real Image Class Transfer



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