Statistical alignment of remote sensing images to improve classifiers portability and change detection

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Motivation

Image classification:

- **Impossible** to carry out terrain campaigns to **obtain ground truth** for **every** acquired **image.** ✗

$\Rightarrow$ Intelligently **reuse** the **information** provided by labeled pixels from similar images. ✓

Change detection:

- **Ambiguity** problem between **changed** and **unchanged pixels.** ✗

$\Rightarrow$ Better representation of the images to **highlight changed regions.** ✓

Motivation

Issues when analyzing multiple remote sensing images:

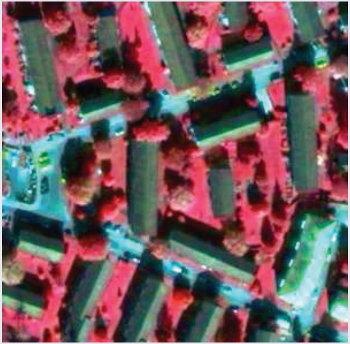
- different illumination,
- changing atmospheric conditions,
- varying acquisition geometry,
- seasonal effects,
- ...

$\Rightarrow$ **shifted probability distributions** between images.

$\Rightarrow$ need to **match/align the images**: physical models (atmospheric correction), histogram matching,...

A concrete example: 2 QuickBird images of Zurich

Source image (autumn)



Target image (summer)

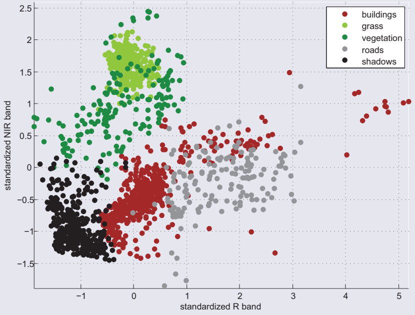
Ground truth

Source image (autumn)

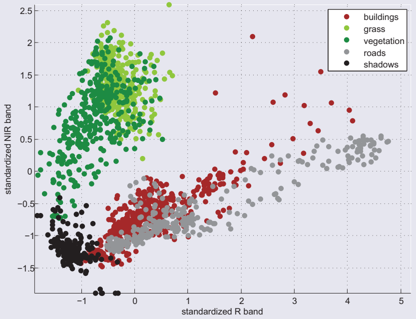
Target image (summer)

Red vs NIR scatterplots

Source training set



Target test set



Objectives

Domain Adaptation via feature extraction

- Map the two images into a feature space where the **differences** are **reduced.**
- Test different **feature extraction** methods (PCA, KPCA, TCA).

Image classification:

$\Rightarrow$ Apply on the target image a **classifier built on labeled source samples** only. ✓

Change detection:

$\Rightarrow$ **Enhanced** quality of the **difference image.** ✓

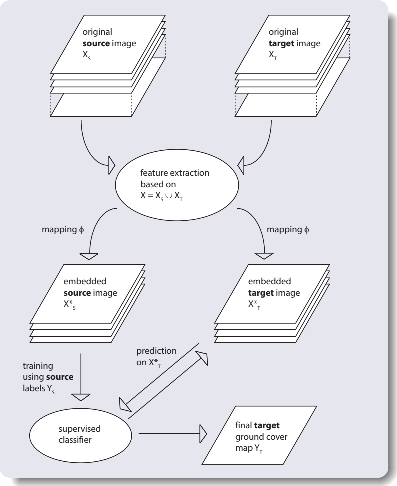
Domain Adaptation via feature extraction: principle

- $\mathcal{D}_S = \{X_S, Y_S\} \rightarrow$ labeled source training data.
- $X_T \rightarrow$ unlabeled target data.
- Find a **common mapping** ϕ (feature extraction techniques: PCA, KPCA, etc.):

$$X_S \rightarrow \phi(X_S) = X_S^*,$$
$$X_T \rightarrow \phi(X_T) = X_T^*.$$

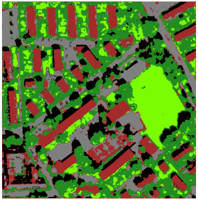
$\Rightarrow$ **Reduce differences between distributions** so that

$$P(X_S^*) \approx P(X_T^*). \checkmark$$

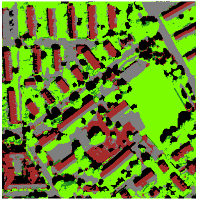


Classification accuracy on target image

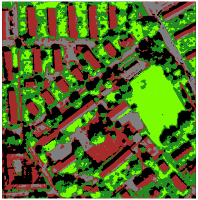
Target image



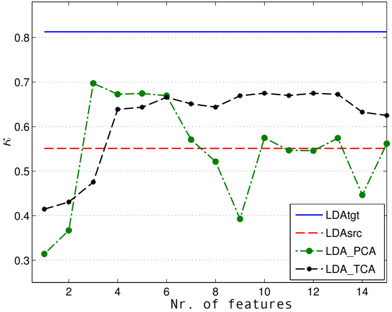
LDAtgt: K = 0.79



LDAsrc: K = 0.54



LDA_TCA: K = 0.68

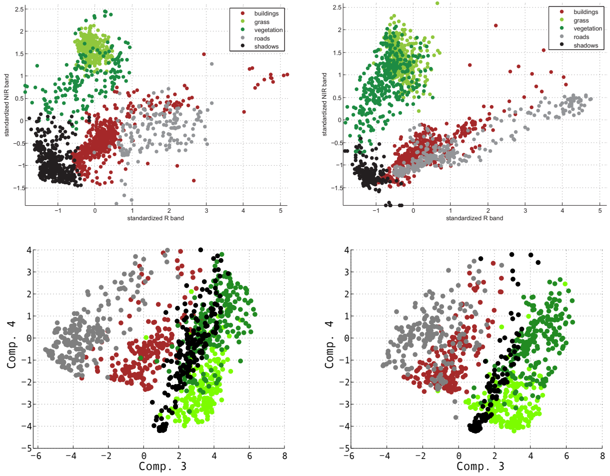


Gain of $\sim 0.15\ \kappa$ points over the Source model (average over 10 runs).

Extracted features

Original R vs NIR

Transformed TCA comps. 3 vs 4



Source image **Target image**

A multitemporal application: change detection

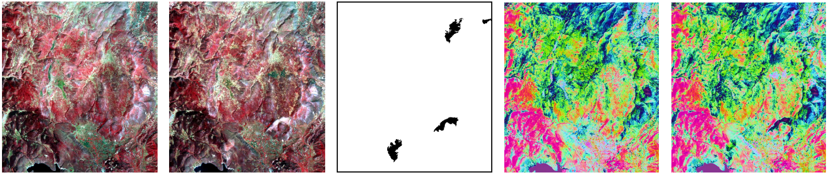
Definitions

- Pixel-based comparison of (co-)registered images to **detect spectral differences** related to **ground cover changes.**
- **Image differencing** (Change Vector Analysis) is the most applied technique:
    - Magnitude of difference pixel vector $< \theta \rightarrow$ **No change.**
    - Magnitude of difference pixel vector $> \theta \rightarrow$ **Change.**

Image alignment in change detection

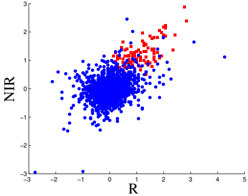
Aligning unchanged areas

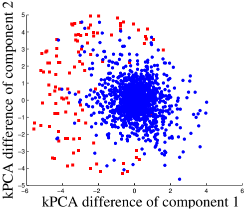
- Based on some ‘no change’ information (easy to obtain) **match the distribution** of images pre- and post-event.
- A **common set of unchanged pixels**, at same locations in both images, is used **to extract the new projection**.
- Physical meaning is lost, but pixel-wise **comparison is improved**.

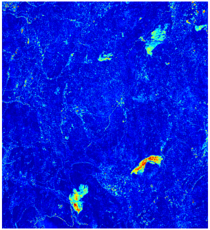


t_1 t_2 GT t_1 transf. t_2 transf.

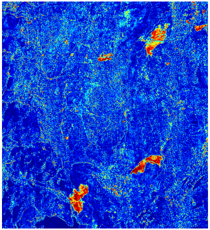
Enhanced difference image representation







original
magnitude



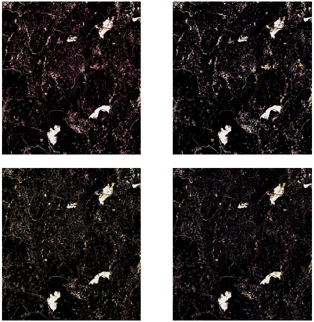
transformed
magnitude

- Even if the magnitude looks ‘noisy’ the **separability** between changes / no changes is **increased**!

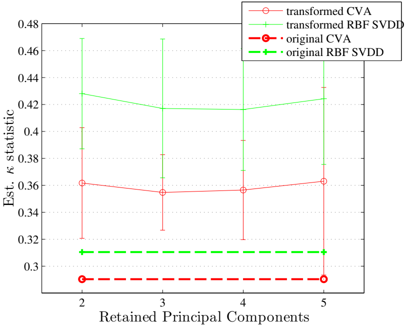
Change detection results

original

transformed



CVA RBF SVDD



- **Improvements over the original space** with different classification techniques: $\sim$0.1 κ points (average over 10 runs).

Summing up

- **Feature extraction** techniques efficiently **align images** in the feature space.

Image classification:

$\Rightarrow$ newly acquired **images** can be suitably **classified** using already **existing ground truth.**

$\Rightarrow$ **classifiers portability** ✓

Change detection:

$\Rightarrow$ the projection **aligns unchanged pixels** emphasizing changed regions.

$\Rightarrow$ **enhanced changed detection** ✓

The end

Thank you for your attention !

Any questions ?

`www.unil.ch/unisciences/GionaMatasci`
`www.kernelCD.org`

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