Graph based data fusion: Application to Change detection and rice crops phenotyping

Pontificia Universidad Javeriana Cali

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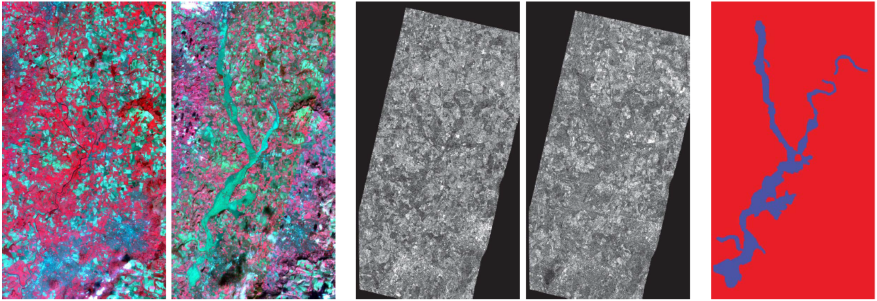
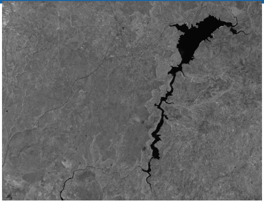
Change detection

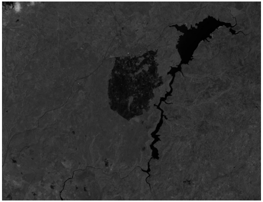


data fusion contest 2009-2010

Challenges in CD



(a) Before event



(b) After event

Satelital images on the red band for fire event near Omodeo lake.

Problems

- Gaussian noise.
- Local brightness distortion.
- Intra-class variation and inter-class variation in the image are relatively small.

Previous work

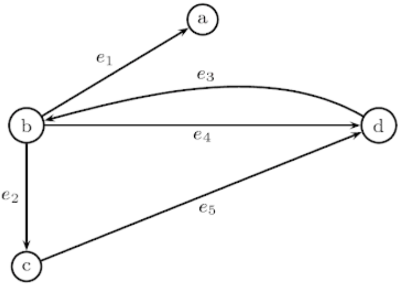
Threshold methods:

- Minimal error [1].
- rayleigh-Rice (rR)[2].
- rayleigh-rayleigh-Rice (rrR)[3].

Machine learning methods:

- Fuzzy clustering [4].
- Genetic algorithm [5].
- Image fusion and fuzzy clustering [6].

Graph



[7]

- The weight w_i, measures or quantify how strong is the relation between nodes, the common measure used for these weights is a Gaussian kernel $w_{i,j} = \exp\left(-\frac{d(V_i,V_j)^2}{\sigma^2}\right)$, where, $d(V_i, V_j)$ is the distances between nodes and σ is the standard deviation of all nodes.

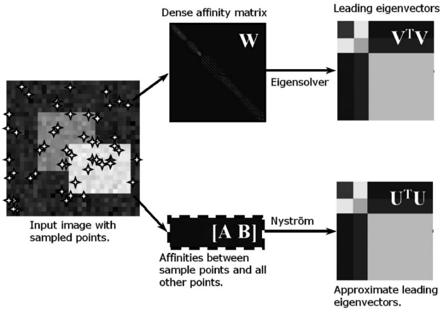
Graph laplacian

A common application of graphs is the embedding of G based on the Laplacian (L) matrix into space $\mathbb{R}^m$, keeping the graph nodes as close as they were on the input space. In short, the embedding of graph is given by the eigenproblem below: [8] :

$$Ly = \lambda Dy, \tag{1}$$

where $L = D - W$, W is known as the adjacency matrix or weights of the graph, D is a diagonal matrix which components are the degree of node ($di = \sum_j w_{i,j}$).

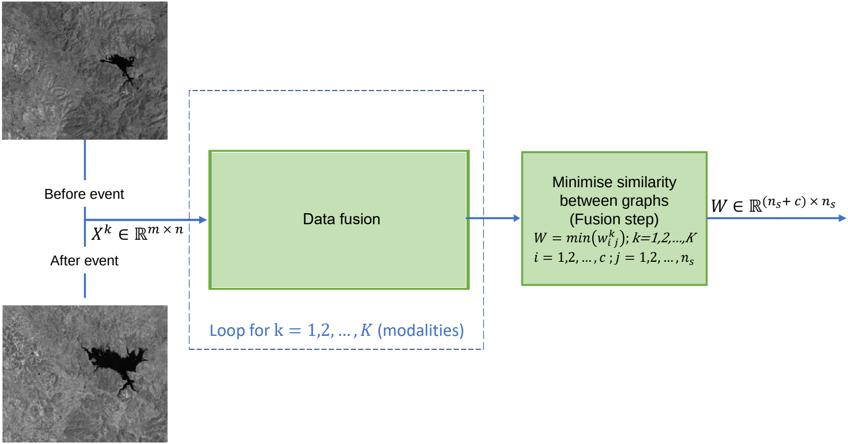
Nyström approximation



Nytröm chart flow[9]

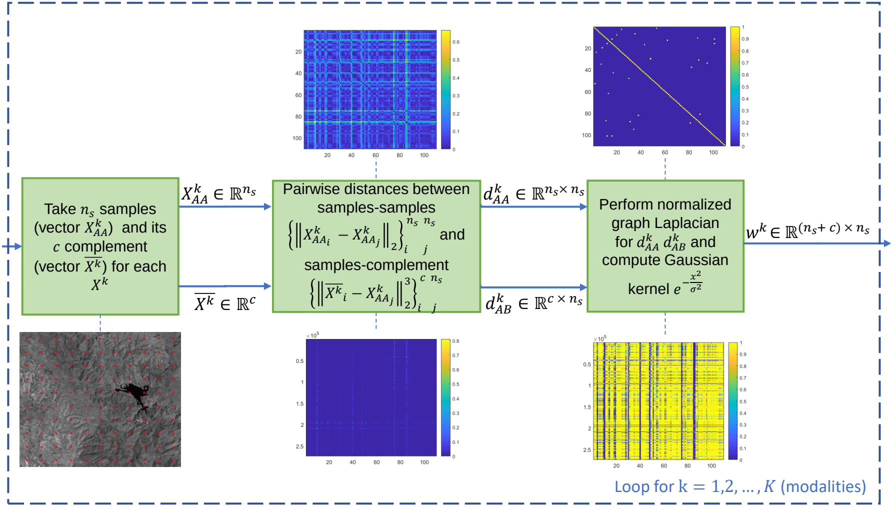
- Take n_s samples.
- Compute distances between samples vs samples (square matrix A) and between samples vs complement (rectangular matrix B).

Chart flow



Multi-modal/temporal graph.

Chart flow



Multi-modal/temporal graph.

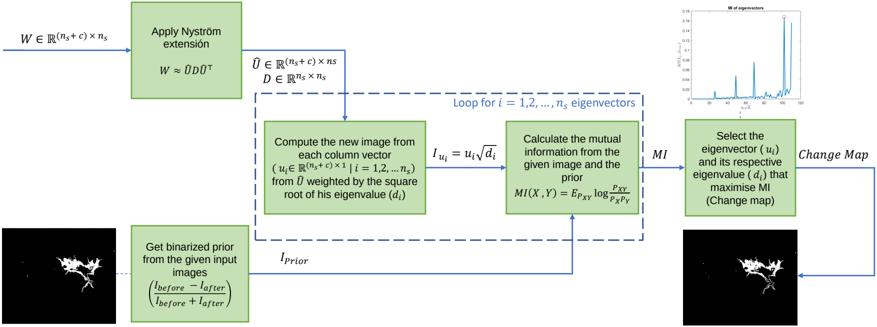
Spectral decomposition

The eigenvectors of the matrix W, can be spanned by eigenvalues and eigenvectors of A (U: $A = U\Lambda U$) by $\hat{U} = \left[U; B^\top U \Lambda^{-1}\right]^\top$.

But the approximated eigenvectors $\hat{U}$ are not orthogonal. In order to get orthogonal eigenvectors is define that $S = A + A^{-\frac{1}{2}} BB^\top A^{-\frac{1}{2}}$, diagonalizing S ($S = U_s \Lambda_s U_s$) the final approximated eigenvectors of W are given by [9] :

$$\hat{U} = \begin{bmatrix} A \\ B^\top A^{-\frac{1}{2}} \end{bmatrix} U_s \Lambda_s^{-\frac{1}{2}}. \tag{2}$$

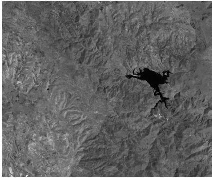
Chart flow for CD



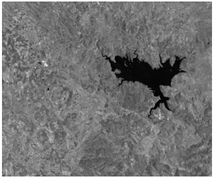
Application of MMT-G for CD.

Databases

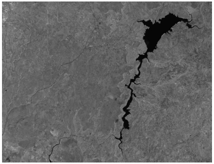
Dataset A (1995 - 1996): Lake Mulargia (Sardinia Island,Italy).
Dataset B (2013): Lake Omodeo (Sardinia Island, Italy).



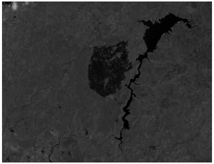
(a) Mulargia lake



(b) F. Mulargia lake



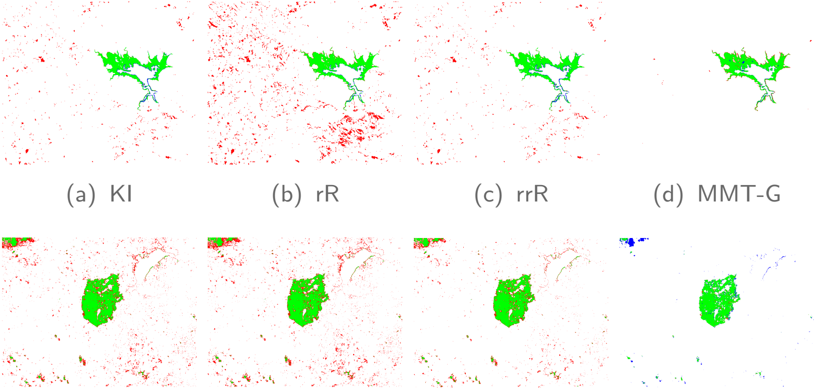
(c) Omodeo lake



(d) Fire event

NIR and Red band respectively.

Qualitative results



(a) KI (b) rR (c) rrR (d) MMT-G

(e) KI (f) rR (g) rrR (h) MMT-G

Change map detected for each model with respect to missed alarms (MA), false alarms (FA) and corrrect changed pixels (C).

Quantitative results

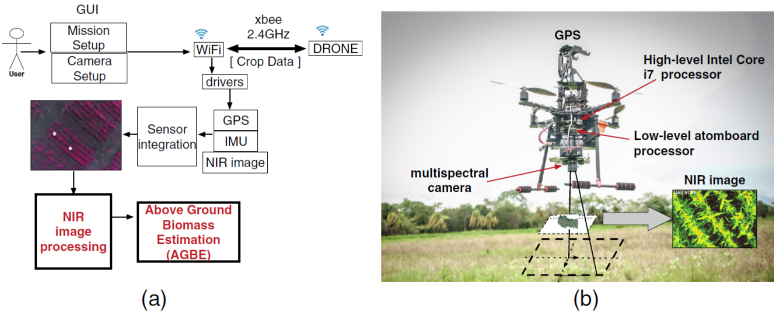
Table: Model Performance for dataset A.

Method	MA (%)	FA (%)	P	R	K	OE (%)
KI [1]	10.2425	1.0490	0.7229	0.8975	0.7941	1.3211
rR-EM [2]	5.7245	4.0147	0.4173	0.9427	0.5605	4.0653
rrR-EM [3]	10.1440	1.0637	0.7203	0.8985	0.7928	1.3324
MMT-G	**4.8504**	**0.3120**	**0.9029**	**0.9515**	**0.9242**	**0.4463**

Table: Model Performance of dataset B.

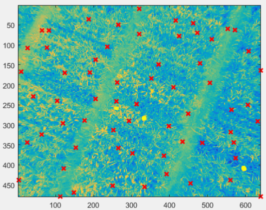
Method	MA (%)	FA(%)	P	R	K	OE (%)
KI [1]	**0**	3.4291	0.5903	**1**	0.7262	3.2676
rR-EM [2]	0.0029	3.7382	0.5693	0.9999	0.7080	3.5623
rrR-EM [3]	0.0029	2.1449	0.6973	0.9999	0.8112	2.0440
MMT-G	14.4217	**0.1226**	**0.9718**	0.8557	**0.9059**	**0.7960**

Rice phenotyping

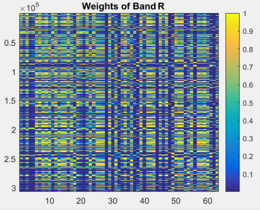


Experimental set-up in [10]

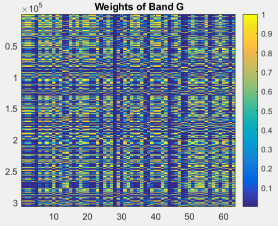
Data fusion of R and G bands



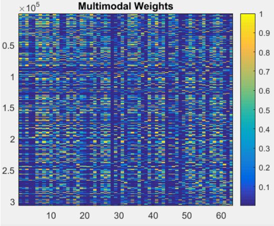
(a) Samples



(b) W of R band

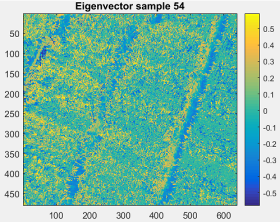


(c) W of G band

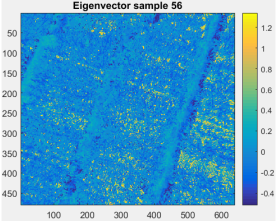


(d) Multi-modal W

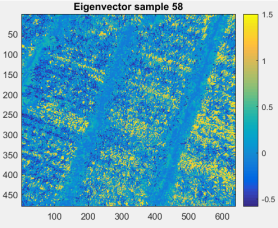
Data fusion of R and G bands



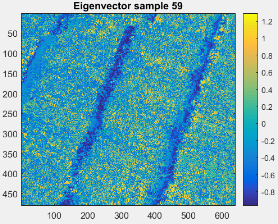
(e) λ_{54}



(f) λ_{56}



(g) λ_{58}



(h) λ_{59}

Concluding remarks

- Deals with the Gaussian noise and local brightness distortion, outperforming threshold methods.
- The results depend on the selection and size of the samples from data (How to select them?).
- Euclidean distance is not enough to measure or capture the differences in data (Try other metrics).

Future work

- Explore the use of graph fourier transform (GFT) in the fusion step.
- Propose and test other kind of metrics as distance in the Gaussian kernel.
- Use some graph signal processing (GSP) techniques (Smoothness, spectral filtering and causal dependencies) to improve performance of the model.

Currently, we are working on a paper "*Multi-modal/temporal graph for change detection in multi-spectral images*", for the International Conference on Acoustics, Speech, and Signal Processing (**ICASSP 2020**) an IEEE Signal Processing Society conference.

Bibliography I

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J. Kittler and J. Illingworth, "Minimum error thresholding," *Pattern recognition*, vol. 19, no. 1, pp. 41–47, 1986.

M. Zanetti, F. Bovolo, and L. Bruzzone, "Rayleigh-rice mixture parameter estimation via em algorithm for change detection in multispectral images," *IEEE Transactions on Image Processing*, vol. 24, no. 12, pp. 5004–5016, 2015.

M. Zanetti and L. Bruzzone, "A theoretical framework for change detection based on a compound multiclass statistical model of the difference image," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 2, pp. 1129–1143, 2017.

A. Ghosh, N. S. Mishra, and S. Ghosh, "Fuzzy clustering algorithms for unsupervised change detection in remote sensing images," *Information Sciences*, vol. 181, no. 4, pp. 699–715, 2011.

T. Celik, "Change detection in satellite images using a genetic algorithm approach," *IEEE Geoscience and Remote Sensing Letters*, vol. 7, no. 2, pp. 386–390, 2010.

M. Gong, Z. Zhou, and J. Ma, "Change detection in synthetic aperture radar images based on image fusion and fuzzy clustering," *IEEE Transactions on Image Processing*, vol. 21, no. 4, pp. 2141–2151, 2011.

G. Alfredo Caicedo Barrero, *Introducción a la Teoría de Grafos*. Elizcom S.a.s. [Online]. Available: https://books.google.com.co/books?id=3hH11r7j1tcC

M. Belkin and P. Niyogi, "Laplacian eigenmaps for dimensionality reduction and data representation," *Neural computation*, vol. 15, no. 6, pp. 1373–1396, 2003.

C. Fowlkes, S. Belongie, F. Chung, and J. Malik, "Spectral grouping using the nystrom method," *IEEE transactions on pattern analysis and machine intelligence*, vol. 26, no. 2, pp. 214–225, 2004.

Bibliography II

C. A. Devia, J. P. Rojas, E. Petro, C. Martinez, I. F. Mondragon, D. Patino, M. C. Rebolledo, and J. Colorado, "High-throughput biomass estimation in rice crops using uav multispectral imagery," *Journal of Intelligent & Robotic Systems*, pp. 1–17, 2019.