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

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Change detection

data fusion contest 2009-2010
Challenges in CD

(a) Before event

(b) After event

Satellite 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].
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 $\sigma$ is the standard deviation of all nodes.
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]:

$$Ly = \lambda Dy,$$

(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 ($d_i = \sum_j w_{i,j}$).
Nyström approximation

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

Nyström chart flow[9]
Chart flow

Before event

\[ X^k \in \mathbb{R}^{m \times n} \]

After event

Minimise similarity between graphs (Fusion step)

\[ W = \min_{i,j,k} w_{ij}^k; k=1,2,\ldots,K \]

\[ i = 1,2,\ldots,c; j = 1,2,\ldots,n_s \]

\[ W \in \mathbb{R}^{(n_s + c) \times n_s} \]

Loop for \( k = 1,2,\ldots,K \) (modalities)

Multi-modal/temporal graph.
Take $n_s$ samples (vector $X^k_{AA}$) and its $c$ complement (vector $X^k$) for each $X^k$.

Pairwise distances between samples-samples:
\[
\left\{ \left\| X^k_{AA_i} - X^k_{AA_j} \right\|_2 \right\}_{i,j}^{n_s \times n_s}
\]

Pairwise distances between samples-complement:
\[
\left\{ \left\| X^k_i - X^k_{AA_j} \right\|_2 \right\}_{i,j}^{c \times n_s}
\]

Perform normalized graph Laplacian for $d^k_{AA} \in \mathbb{R}^{n_s \times n_s}$ and compute Gaussian kernel $e^{-\frac{x^2}{\sigma^2}}$.

$W^k \in \mathbb{R}^{(n_s + c) \times n_s}$

Loop for $k = 1, 2, ..., K$ (modalities)

Multi-modal/temporal graph.
Spectral decomposition

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

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

$$\hat{U} = \begin{bmatrix} A \\ B^TA^{-1/2} \end{bmatrix} U_sΛ_s^{-1/2}. \quad (2)$$
Application of MMT-G for CD.

Chart flow for CD

1. **Apply Nyström extension**
   
   \[ W \approx \bar{U}D\bar{U}^\top \]

2. **Compute the new image from each column vector**
   
   \[ I_u = u_i \sqrt{d_i} \] from \( \bar{U} \) weighted by the square root of his eigenvalue \( d_i \).

3. **Get binarized prior from the given input images**
   
   \[ I_{\text{Prior}} = \left( \frac{I_{\text{before}} - I_{\text{after}}}{I_{\text{before}} + I_{\text{after}}} \right) \]

4. **Calculate the mutual information from the given image and the prior**
   
   \[ MI(X,Y) = E_{P_{XY}} \log \frac{P_{XY}}{P_XP_Y} \]

5. **Select the eigenvector \( u_i \) and its respective eigenvalue \( d_i \) that maximise MI**
   
   \( \text{(Change map)} \)

6. **Loop for** \( i = 1, 2, \ldots, n_s \) **eigenvectors**

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**Application of MMT-G for CD.**
Databases

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

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

**Table:** Model Performance for dataset A.

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

**Table:** Model Performance of dataset B.

<table>
<thead>
<tr>
<th>Method</th>
<th>MA (%)</th>
<th>FA (%)</th>
<th>P</th>
<th>R</th>
<th>K</th>
<th>OE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>KI [1]</td>
<td>0</td>
<td>3.4291</td>
<td>0.5903</td>
<td>1</td>
<td>0.7262</td>
<td>3.2676</td>
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<tr>
<td>rR-EM [2]</td>
<td>0.0029</td>
<td>3.7382</td>
<td>0.5693</td>
<td>0.9999</td>
<td>0.7080</td>
<td>3.5623</td>
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<tr>
<td>rrR-EM [3]</td>
<td>0.0029</td>
<td>2.1449</td>
<td>0.6973</td>
<td>0.9999</td>
<td>0.8112</td>
<td>2.0440</td>
</tr>
<tr>
<td>MMT-G</td>
<td>14.4217</td>
<td><strong>0.1226</strong></td>
<td><strong>0.9718</strong></td>
<td>0.8557</td>
<td><strong>0.9059</strong></td>
<td><strong>0.7960</strong></td>
</tr>
</tbody>
</table>
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) \( \lambda_{54} \)

(f) \( \lambda_{56} \)

(g) \( \lambda_{58} \)

(h) \( \lambda_{59} \)
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.

Bibliography I


