Multimodal Data Processing

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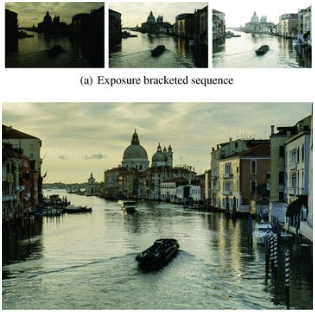
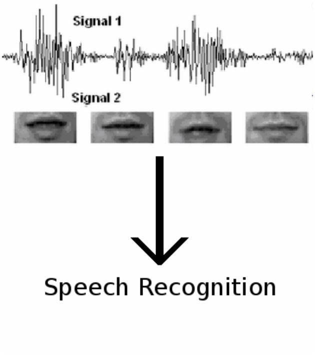
Overview

Multimodal datasets

With the increasing availability of data, many applications involve data drawn from more than one source (called *modalities*).


(a) Exposure bracketed sequence
(b) Fused result



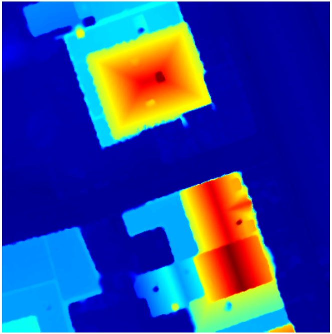
Exposure Fusion:
[Mertens et al, CGF, 2008]

Speech Recognition:
[Datcu et al, IEEE CVPR 2007]

Example Multimodal Data

Remote sensing example: RGB + Elevation map.
From 2015 IEEE Data Fusion Contest.
[Bampos-Taberner et al, IEEE J-STARS 2016]

RGB Data



Lidar Data

Challenges in multimodality

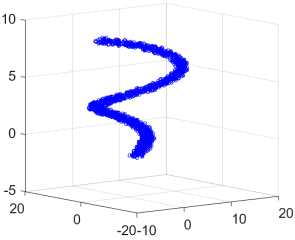
Most multimodal methods are developed specifically for one problem, BUT:

[Lahat et al, IEEE 2015]: "... a solution that is based on a sufficiently data-driven, model-free approach may turn out to be useful in very different domains."

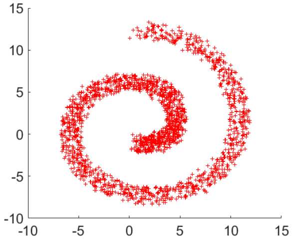
Manifold alignment

Attempt to address multimodality in general.

For each modality, view the data as a manifold
(have sets $X^1, X^2, \ldots, X^\ell$. $\ell =$ number of modalities).

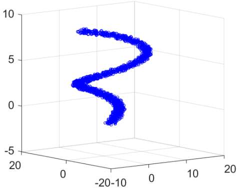


X^1

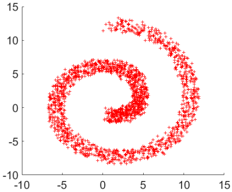


X^2

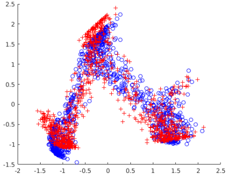
Create a *latent space* Y and maps $X^i \to Y$.



X^1



X^2



Images in latent space

Example from [Tuia et al, PLOS ONE 2016]

Compare sets by using the latent space image.

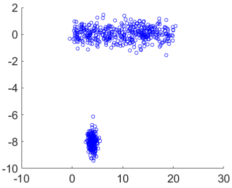
Manifold alignment: Methods from the literature

Some examples from the literature:

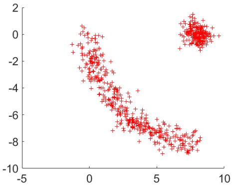
- [Yeh et al, IEEE TIP 2014]: Canonical Correlation Analysis, linear or with nonlinear kernel (unsupervised)
- [Wang et al, IJCAI 2013]: Graph-based methods (semi-supervised)
- [Tuia et al, PLOS ONE 2016]: Similar to the above with an added nonlinear kernel (semi-supervised)

Manifold alignment: Methods from the literature

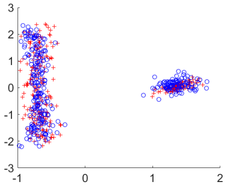
Common theme: Create the latent space by finding and correlating *redundancies* between sets.



X^1



X^2



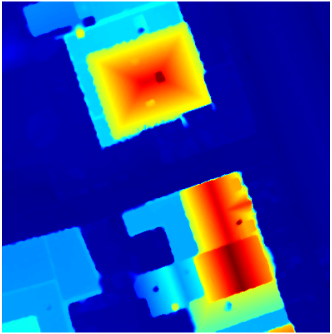
Images in latent space

Using code from [Tuia et al, PLOS ONE 2016]

Manifold alignment: Our goal

Our idea: Can improve on these methods. Find and exploit the unique information that each modality brings.

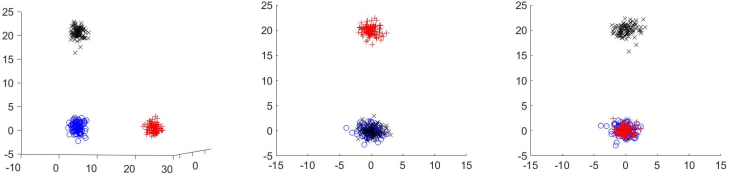
Distinguish road from grass



Distinguish roof from ground

Synthetic example: Data

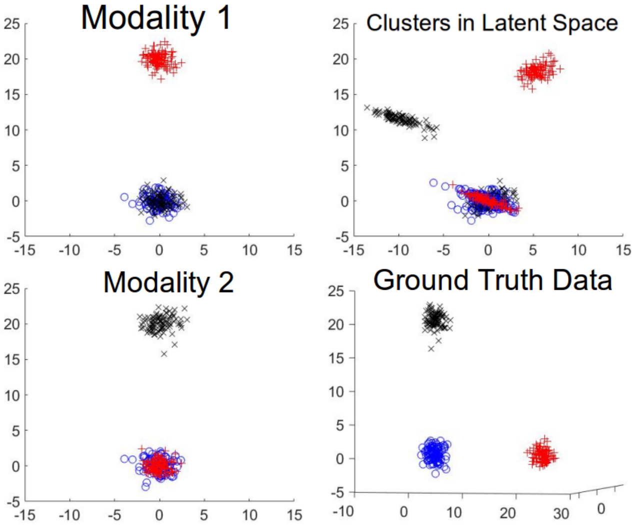
Ground truth = 3 point clouds in $\mathbb{R}^3$ (100 points per cloud).
Modality 1 = projection onto *xy*-plane.
Modality 2 = projection onto *xz*-plane.
Co-registration assumption: index is input to algorithm.



Underlying Data Modality 1 Modality 2

Synthetic Example: Result of CCA

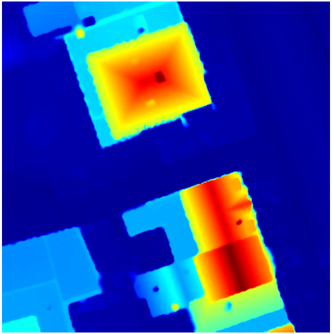
Result of CCA algorithm from [Yeh et al, IEEE TIP 2014]:



Problem setup

We use co-registration assumption and graph Laplacian theory for segmentation of multimodal datasets.
[Iyer et al., Accepted Paper, ICIP 2017]

RGB Data



Lidar Data

Notation

From each modality, have a data set X^k. $\ell =$ number of modalities.

$N =$ number of observations.

$d_j =$ dimension of set X^k. (Can view $X^k \in \mathbb{R}^{N \times d_k}$).

From co-registration assumption:
i-th point in X^{k_1} corresponds to i-th point in X^{k_2}.
Create concatenated set $X = (X^1, X^2, \ldots, X^\ell) \subseteq \mathbb{R}^{N \times (d_1 + \cdots + d_\ell)}$.

$x_i =$ element i from X. $x_i^k =$ element i from X^k.

Graph Representation: Background

When using a single modality:

For each pair $x_i, x_j \in X$, define a *weight* w_{ij} that measures the similarity between the points.

$\implies$ represent data as $N \times N$ weight matrix W.

Common similarity measure from the literature: RBF kernel

$$w_{ij} = \exp\left(- \left\|x_i - x_j\right\|^2 / \sigma\right).$$

Need to adapt this to multimodal data.

Multimodal Weight Matrix

For each modality X^k, calculate the distance matrix E^k via

$$E_{ij}^k = \left\| x_i^k - x_j^k \right\|.$$

$\|\cdot\|$ chosen based on the details of the modality.

(in our examples $\|\cdot\|$ is the 2-norm)

Scale each matrix by standard deviation (nondimensionalization)

$$\bar{E}^k = \frac{E^k}{\operatorname{std}\left(E^k\right)}.$$

Multimodal Weight Matrix

Define

$$w_{ij} = \exp\left(-\max\left(\bar{E}_{ij}^{1}, \ldots, \bar{E}_{ij}^{k}\right)/\sigma\right).$$

Heuristics:

- Standard deviation scaling allows us to directly compare $\bar{E}^{k_1}, \bar{E}^{k_2}$ with reasonable results.
- Because of the max, elements are similar under this measure only if they are similar in each modality.

Graph min-cut

Use weights W to segment X into $A_1, \dots, A_k$. We want to

- group nodes with high similarity (weight) together
- ensure each set is a reasonable size

Use the *Normalized graph-cut*

$$\mathrm{Ncut}(A_1, \dots, A_k) = \frac{1}{2} \sum_{j=1}^{k} \frac{W(A_j, A_j^c)}{vol(A_j)}.$$

$$W(A, B) = \sum_{i \in A, j \in B} w_{ij}.$$

$$vol(A) = \sum_{i \in A, j \in X} w_{ij}.$$

Exact min-cut solution is computationally infeasible.

Graph Laplacian

A well-known approximation for graph min-cut:
eigenvectors of the graph Laplacian L.

$$L = I - D^{-1/2} W D^{-1/2},$$

where $D = N \times N$ diagonal matrix (degree matrix), with

$$d_{ii} = \sum_{j=1}^{n} w_{ij}.$$

Feature extraction

Result of [vonLuxburg, Stat Comput 2007]

$$\text{eigenvectors of } L \iff \text{features extracted from data}$$

Can use eigenvectors for a variety of applications.

Our results: K-means on eigenvectors $\rightarrow$ segmentation
(this is called Spectral Clustering).

Future work: Apply graph MBO [Merkurjev, SIIMS 2013] instead.

Nyström Extension

As $|X|$ becomes large, computing the $|X| \times |X|$ weight matrix W becomes prohibitive.

Instead choose $A \subseteq X$ *landmark nodes* with $|A| \ll |X|$. Up to permutation, we have

$$W = \begin{pmatrix} W_{A,A} & W_{A,A^c} \\ W_{A^c,A} & W_{A^c,A^c} \end{pmatrix}.$$

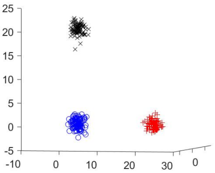
[Fowlkes et al., IEEE TPAMI 2004]:
Approximate graph Laplacian eigenvectors using only $W_{A,A}$, $W_{A^c,A}$.

$$W \approx \begin{pmatrix} W_{A,A} \\ W_{A^c,A} \end{pmatrix} W_{AA}^{-1} \begin{pmatrix} W_{A,A} & W_{A,A^c} \end{pmatrix}.$$

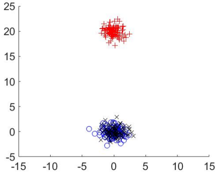
Compute and store matrices of size at most $|X| \times |A|$.

Synthetic example: Data

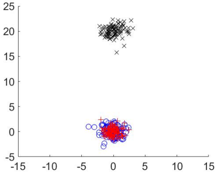
Synthetic example:
Ground truth = 3 point clouds in $\mathbb{R}^3$ (100 points per cloud).
Modality 1 = projection onto xy-plane.
Modality 2 = projection onto xz-plane.



Ground Truth



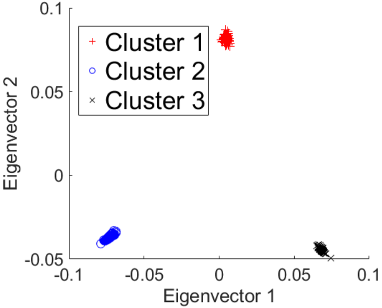
Modality 1



Modality 2

Synthetic Example: Result of Our Method

Result of our multimodal graph-based algorithm on earlier example: Plotting first 2 eigenvectors.

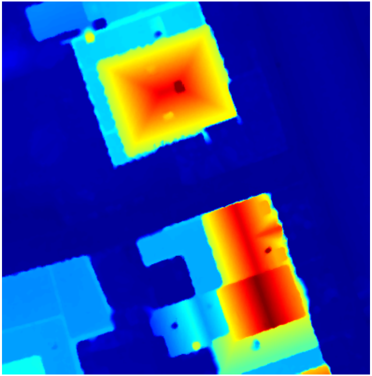


2 eigenvectors of graph Laplacian

Data

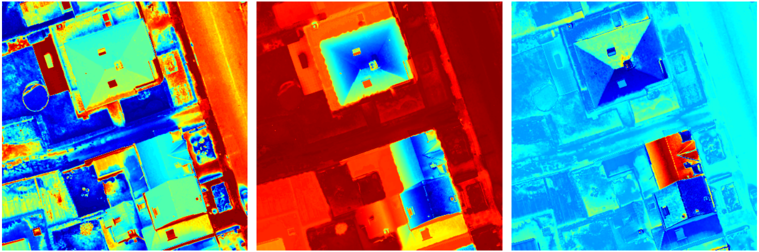
Our algorithm applied to
[Bampos-Taberner et al, IEEE J-STARS 2016] dataset.

RGB Modality



Lidar Modality

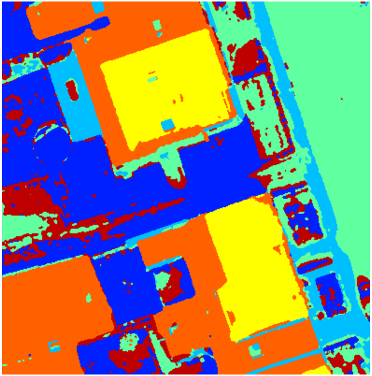
Results



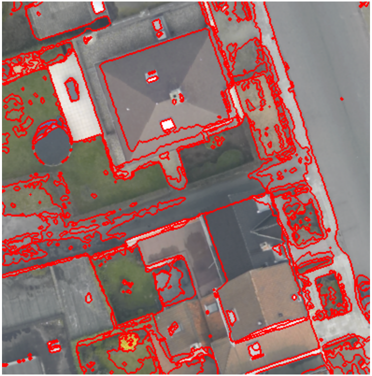
Example eigenvectors of graph Laplacian

Results

Spectral Clustering result (unsupervised). $m = 6$ classes.



Classes

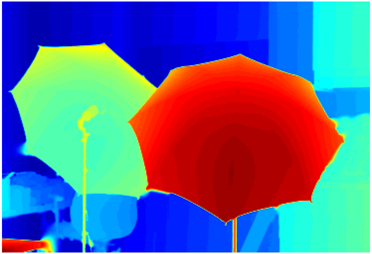


Regions on original image

Data

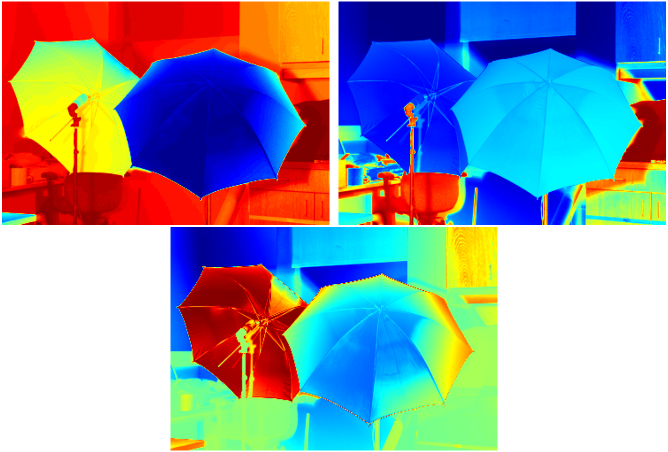
Our algorithm applied to [Scharstein et al., GCPR 2014] dataset.

RGB Modality



Lidar Modality

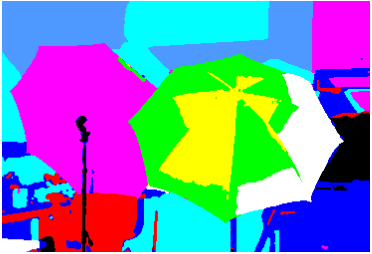
Results



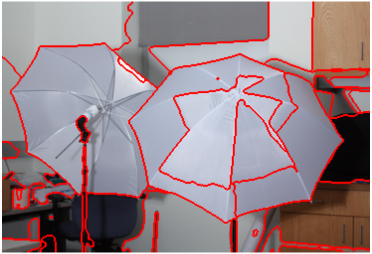
Example eigenvectors of graph Laplacian

Results

Spectral Clustering result (unsupervised). $m = 8$ classes.



Classes



Regions on original image

Graph Matching

Goal: Remove or weaken the coregistration assumption.

Current idea: Graph matching.

View each dataset as a (weighted) graph.
Try to match nodes with similar structure.

Problem Setup

Two weighted graphs, G_1, G_2, with weight matrices W_1, W_2.

For now, $|G_1| = |G_2| = N$.

Search for a graph isomorphism $G_1 \to G_2$ preserving edge weights.

Best isomorphism is $1 \to 2$, $2 \to 3$, $3 \to 1$.

Problem Setup

Isomorphism $G_1 \to G_2$ corresponds to a permutation on nodes. Have P the corresponding permutation matrix. Want to minimize

$$\left\| W_1 - P W_2 P^T \right\|_F^2 .$$

Exact solution is too expensive. Can solve using graph Laplacian trick from
[Umeyama, IEEE TPAMI 1988, Knossow et al., GbRPR 2009].

Relaxation

Relax problem to

$$Q^* = \text{argmin}_{QQ^T=I} \left\| W_1 - QW_2Q^T \right\|_F^2 .$$

Let L_1, L_2 the graph Laplacians corresponding to W_1, W_2

U_1, U_2 the corresponding matrices of eigenvectors.

Then $Q^* = U_1 S U_2^T$.

S is a diagonal matrix with entries of ± 1 to account for sign ambiguity in eigenvectors.

Heuristics

Recall from graph Laplacian

$$\begin{aligned} \text{column of } U_i &\iff \text{feature extracted from data} \\ \text{row of } U_i &\iff \text{image of data point in new feature space.} \end{aligned}$$

Match rows of U_1 to rows of U_2 by considering $U_1 U_2^T$.

Matching Algorithm

Q^*_{ij} gives the similarity between node i of G_1 and node j of G_2.

Choose a permutation $p : \{1, 2, \ldots, N\} \to \{1, 2, \ldots, N\}$ via

$$\text{argmax}_{\text{permutations } p} \sum_{i=1}^{N} Q^*_{i,p(i)}.$$

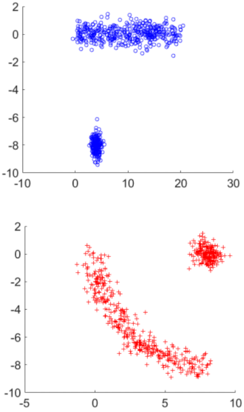
Hungarian algorithm finds this in $O(N^3)$ [Munkres, SIAM 1957].

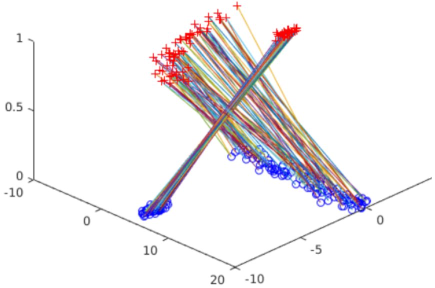
Benefits of Graph Matching

Benefits of Graph Matching

1. Invariant under conformal maps.
   - scaling, shifts, rotations, etc.
   - robust to continuous deformation.
2. A precise number representing similarity between nodes gives us many options.
   - Thresholding
   - Hierarchical matching
3. Easy extension to the case $|G_1| \neq |G_2|$.

Example Matching





Graph Match on Synthetic Data

Change Detection

One possible application: Change detection.

Given images X and Y of the same scene, compare coregistration against results of graph matching. Use this to pick out large changes between X, Y.

From graph matching, get a permutation

$$\rho : \{1, \ldots, n\} \to \{1, \ldots, n\}.$$

Compare x_i to $x_{\rho(i)}$, and y_i to $y_{\rho(i)}$.

Change Detection Example

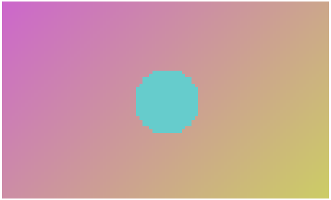


Image X

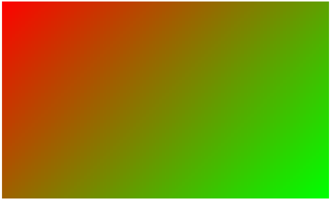
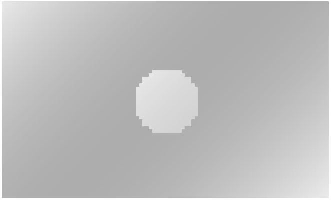
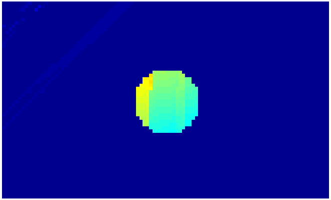


Image Y



Naive difference $\|X - Y\|$



$\left\| x_i - x_{\rho(i)} \right\|$

Future directions

Possible directions for future work

1. Improve image segmentation using graph MBO.
2. Change detection using graph matching.
3. Push performance of graph matching.

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