Toward semantic segmentation based on Community detection in Graphs

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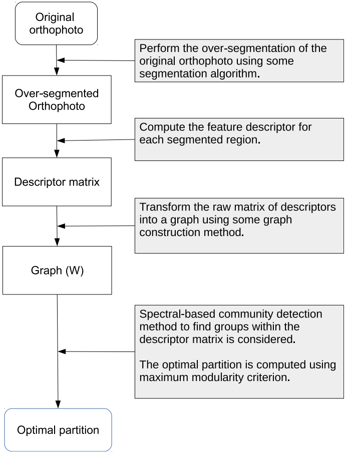
January 25, 2017

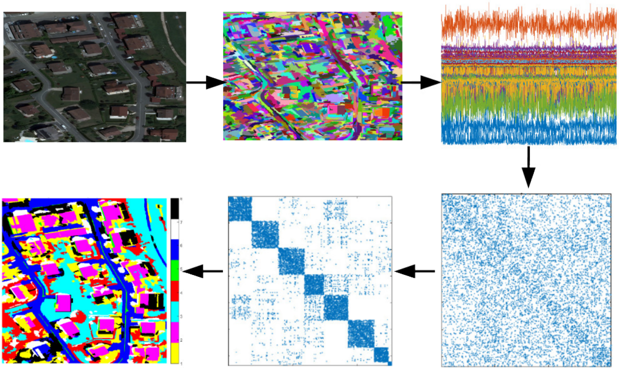
Overview

Flow diagram



Flow diagram of the full automatic detection of regions of interest (ROIs) in orthophotos: The framework broadly follows a four-step procedure: image over-segmentation, feature descriptors extraction, graph construction, and community detection

Graphical illustration



For the task of automatic scene parsing, the supervised approaches need training images in which a set of images are delineated and labeled by categories.

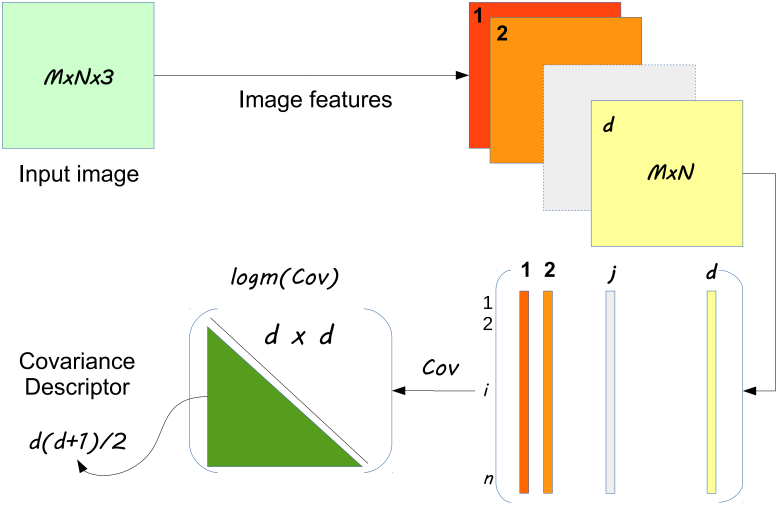
Orthophotos

- 12 large orthophotos depicting several zones in the region of Belfort city situated on the north-eastern of France.
- The spatial resolution of these orthophotos, provided by Communauté de l'Agglomération Belfortaine (CAB 2008), is (1 pixel=16 cm).
- These orthophotos contain about 200 buildings. In these orthophotos, the building roofs have different colours and textures.
- The background contains highly varying appearances corresponding to vegetation, cars, roads, and other objects.

Some popular segmentation algorithms

- Watershed Algorithm
- Statistical Region Merging (SRM)
- Mean shift algorithm (MS)
- Superpixels algorithm

Covariance descriptors



Covariance descriptor

In our work, we consider 23 image features, i.e., $d = 23$.

- x and y coordinates
- 6 image derivatives
- 6 color channels both in RGB and HSV spaces
- 9 Local Binary Pattern images obtained by combining three different modes and three radii

For all LBP images, the number of neighboring points is fixed to 8. Since the number of channels used is 23, it follows that the descriptor of each segmented region is described by 23 * 24 / 2 = 276 features.

Color histograms is computed quantizing uniformly each color channel into 16 bins resulting in a descriptor of size given by 4096 bins.

Given n points $\mathbf{x}_i, ..., \mathbf{x}_n$ in R^d

1. Constructing the adjacency graph from data: We put an edge between nodes i and j if $\mathbf{x}_i$ and $\mathbf{x}_j$ are "close" (ϵ-neighborhoods with $\epsilon \in R$ and k-nearst neighbors, k $\in N$).
2. Estimating the weights of the graph edges: if nodes i and j are connected, put

$$W_{ij} = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\sigma}}$$

otherwise, $W_{ij} = 0$.

Given n points $\mathbf{x}_i, ..., \mathbf{x}_n$ in R^d

1. Discovering the adjacency information. For each $\mathbf{x}_i$, find the k-nearest neighbors in the data set, $\mathbf{x}_{i1}, ..., \mathbf{x}_{ik}$ (this subset could be data points contained in an $\epsilon - ball$ around $\mathbf{x}_i$.
2. Compute the weights W_{ij} that best linearly reconstruct each $\mathbf{x}_i$ from its neighbors, solving the constrained least-squares problem:

$$\sum_{i=1}^{n} \|\mathbf{x}_i - \sum_{j=1}^{k} W_{ij}\,\mathbf{x}_j\|^2$$

subject to $\mathbf{W1}_n = \mathbf{1}_n$, $\mathbf{W} \geq 0$

Community detection

Community detection

Community detection differs from graph partitioning in that the number and size of the groups into which the graph is divided are not specified in advance, which makes this method more suitable to solve real situations. In fact, community detection is more often used as a tool for understanding the structure of a network, for shedding light on large-scale patterns of connection that may not be easily visible in the raw network topology.

Spectral modularity maximization problem

Assortative mixing

A network is **assortative** if a significant fraction of the edges in the network run between vertices of the same type.

$$Q = \frac{1}{2m}\sum_{ij}(W_{ij} - \frac{k_i k_j}{2m})\delta(c_i, c_j)$$

k_i (k_j) is the degree of node i (j), $m = \sum_{ij} W_{ij}$ is the total number of edges in the network and $\delta(c_i, c_j)$ is the Kronecker delta.
This quantity Q is called the **modularity** and is a measure that has high value when many edges in a graph fall between vertices of the same group than one would expect by chance.

Spectral modularity maximization problem

The quantity,

$$B_{ij} = W_{ij} - \frac{k_i k_j}{2m}$$

is called **modularity matrix**. Note that B_{ij} has the property

$$\sum_j B_{ij} = \sum_j W_{ij} - \frac{k_i}{2m} \sum_j k_j = k_i - \frac{k_i}{2m} 2m = 0$$

Spectral modularity maximization problem

Let $\mathbf{S} = (\mathbf{s}_c)$ be an $n \times C$ membership matrix defined as:

$$S_{ic} = \begin{cases} 1 & \text{if node i is in community c,} \\ 0 & \text{otherwise} \end{cases}$$

$$Q = \frac{1}{2m} Tr(\mathbf{s}^T \mathbf{B} \mathbf{s}),$$

$$Q = \frac{1}{2m} \sum_{i=1}^{n} \sum_{c=1}^{C} \beta_i (\mathbf{v}_i^T s_c)^2,$$

where $V = (\mathbf{v}_1, \mathbf{v}_2, ...)$ is the matrix of eigenvectors of $\mathbf{B}$, and β_i is the eigenvalue corresponding to $\mathbf{v}_i$.

Spectral modularity maximization algorithm

Therefore, to reveal the community structure of the similarity graph, we proceed as follows:

1. we retain the μ eigenvectors corresponding to the largest positive eigenvalues,
2. we iterate over $j = 1, ..., \mu$, spanning the whole range of possible groups.
   - we run a K-means algorithm on the retained eigenvectors looking for a partition into $K = j + 1$ groups.
   - we compute the corresponding modularity $Q(j)$
3. we chose the optimal partition as the one with the maximum modularity $max(Q)$.

Results

Table: Miss-classification error (MCE) and entropy (associated with the building roofs) have been used as supervised measures to quantify the performance of clustering.

Modularity			
	B	K-medoids	K-means
Knn	0.72	-	-
LLE	0.73	-	-

MCE			
	B	K-medoids	K-means
Knn	0.27	0.41	0.60
LLE	0.26	0.43	0.44

Entropy			
	B	K-medoids	K-means
Knn	0.17	0.26	0.31
LLE	0.18	0.27	0.26

Results

Table: The performance measures associated with roofs detection

Accuracy			
	B	K-medoids	K-means
Knn	95.24	92.63	88.94
LLE	95.31	91.87	91.70

F1 measures			
	B	K-medoids	K-means
Knn	84.53	74.56	57.09
LLE	84.84	72.90	71.43

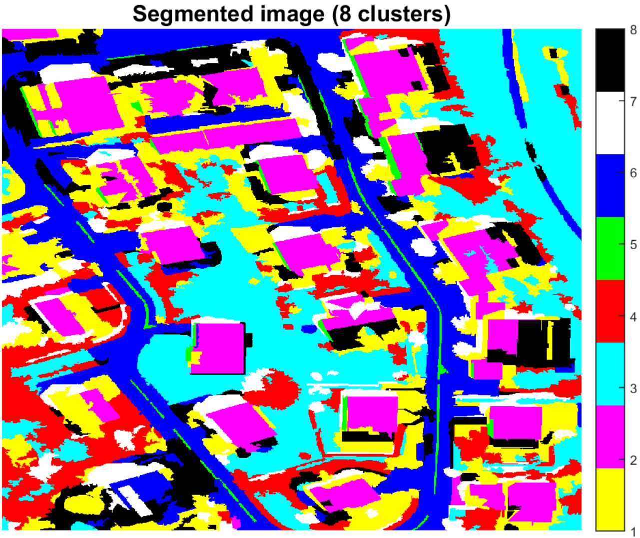
Matthews correlation coefficients (MCC)			
	B	K-medoids	K-means
Knn	0.82	0.72	0.55
LLE	0.83	0.69	0.68

Results

Table: Proximity matrix reporting distances between clusters for a partition of the orthophoto into 8 clusters.

Clust.	1 (y)	2 (m)	3 (c)	4 (r)	5 (g)	6 (b)	7 (w)	8 (k)
1 (y)	0	4.66	5.30	3.05	5.26	4.32	3.64	3.06
2 (m)	-	0	5.21	4.54	5.71	3.38	3.31	5.38
3 (c)	-	-	0	**2.75**	4.97	3.11	5.34	7.63
4 (r)	-	-	-	0	4.69	3.42	3.40	5.78
5 (g)	-	-	-	-	0	3.98	5.83	6.31
6 (b)	-	-	-	-	-	0	4.55	5.56
7 (w)	-	-	-	-	-	-	0	5.22
8 (k)	-	-	-	-	-	-	-	0

Flow diagram



Results

Roofs

Roads

Results

Vegetation

Vegetation

References

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