Lecture 24 Image Segmentation by Clustering ECEN 5283 Computer Vision

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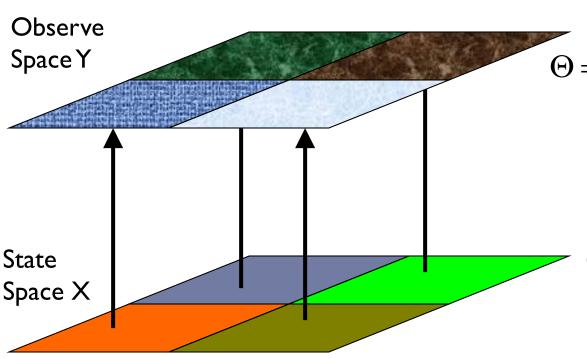
Goals



- ▶ To review the Expectation Maximization (EM) algorithm and compare EM with K-means.
- To introduce Project 4, image segmentation that involves texture analysis and clustering.

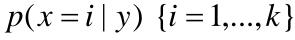
Missing Data Problem





Parameter Space

$$\Theta = \{\alpha_i, \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i \mid i = 1, 2, 3, 4\}$$



(posterior probability)

Can be computed but not easy to optimize

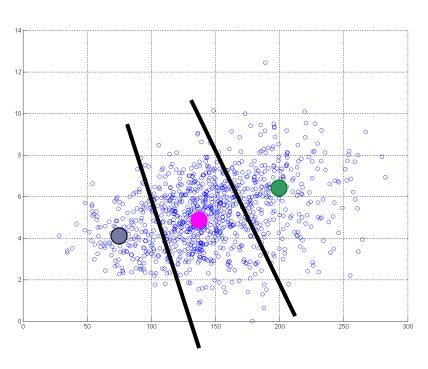
Cannot be computed but can be optimized via a lower bound

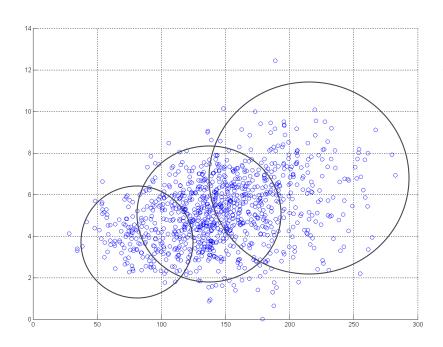
 $\Theta^* = \arg \max_{\Theta} \log p(Y \mid \Theta)$ (log - likelhood of incomplete data)

 $\Theta^* = \arg \max_{\Theta} \log p(X, Y | \Theta)$ (log-likelhood of completedata)

K-means vs. EM

$$\mathbf{Y} = (y_1, y_2, ..., y_N) \rightarrow \mathbf{X} = (x_1, x_2, ..., x_N)$$





$$x_i = \arg_{j \in \{1, \dots, k\}} \min |y_i - \mathbf{c}_j|$$

$$x_i = \arg_{j \in \{1,\dots,k\}} \max p(x_i = j \mid y_i, \Theta)$$

K-mean vs. EM



▶ Both K-means and EM need to be initialized and involve two major steps during iteration.

	K-mean	EM
Initialization	Initialize k means (cluster centers)	Initialize k Gaussian models that have equal weights.
	$C^0 = \{\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k\}$	$\Theta^0 = \{\alpha_i, \mu_i, \sum_i i = 1, \dots, k\}$
Step I.	Assume the cluster centers are known, and classify each data sample to the closest cluster center.	Given the model parameters, estimate the missing data in terms of the posterior probability of each data sample.
Step 2.	Assume the allocation is known, and choose a new set of cluster centers. Each center is the mean of the points allocated to that cluster.	From the estimated missing data, to obtain the maximum likelihood estimate of the model parameters.

EM Algorithm: Initialization by K-means



$$C^0 = \{\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k\}$$

Run the k-means for each initialization until converge or with certain iteration number, and picks the best K-means result.

$$\Phi(\mathbf{X}, \mathbf{Y}) = \sum_{i=1}^{k} \left\{ \sum_{x_j=i} \left| y_j - \mathbf{c}_i \right|^2 \right\}$$

According to the class label of all samples $\{x_1, x_2, ..., x_N\}$, initialize the multivariate Gaussian models for the EM.

$$\alpha_{i} = \frac{\#(x_{j} = i \mid j = 1,...,N)}{N}$$

$$\sum_{x_{j} = i} y_{j}$$

$$\mu_{i} = \frac{\sum_{x_{j} = i} y_{j}}{\#(x_{i} = i \mid j = 1,...,N)}$$

$$\sum_{i} = \frac{\sum_{x_{j} = i} (y_{j} - \mu_{i})(y_{j} - \mu_{i})^{T}}{\#(x_{j} = i \mid j = 1,...,N)}$$



EM Algorithm: Additional Issues

Initialization:

- Both EM and K-mean only converge to the local optimum.
- Using K-mean is a practical way to initialize the EM algorithm.

Iteration:

Iteration still the stop criteria is satisfied, e.g., no much change of the incomplete data log-likelihood

$$p(Y | \Theta^{(s+1)}) - p(Y | \Theta^{(s)}) < \Delta \rightarrow \log p(Y | \Theta^{(s+1)}) - \log p(Y | \Theta^{(s)}) < \Delta'$$

Or the iteration number can be fixed as a constant.

Data classification

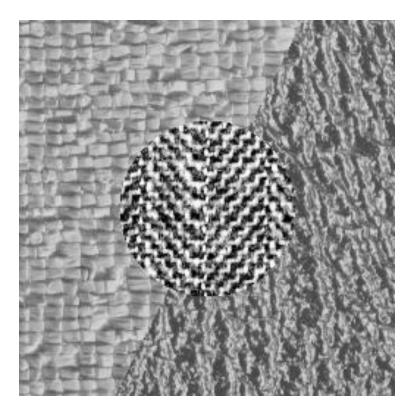
MAP classification

$$x_l = \arg_{m \in \{1, \dots, g\}} \max \mathbf{I}(l, m)$$



Image Segmentation

▶ The goal of image segmentation is to segment an image into G homogeneous regions.



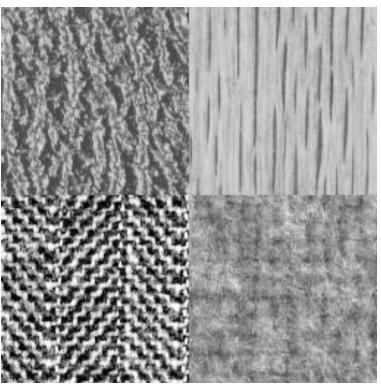




Image Segmentation by Clustering

Problem Formulation

An image has totally N pixels each of pixel is associated with a feature vector $Y = (y_l | l = 1,..., N)$, and the question is what is the class label for each pixel $X = (x_l | l = 1,..., N)$?

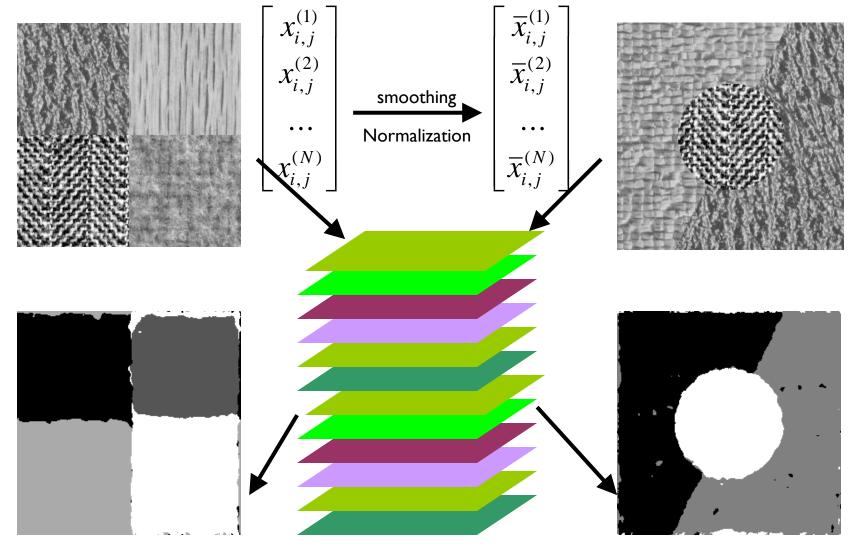
Assumption

It is assumed that feature vectors of G classes are defined by G multivariate Gaussians $\Theta = \{\alpha_m, \theta_m = (\mu_m, \Sigma_m) | m = 1,..., G\}$ that defines the distribution of feature vectors and the ratio of each class.

Solution:

Image segmentation becomes a clustering problem that can be solved by K-means or EM.

Feature Extraction: Gabor Filtering



Segmentation Evaluation



function Per=accuracy(Truth,Result,Num);

% Truth is the groud-truth map, Result is the obtained map, Num is the number class

% Per is the segmentation accuracy

[XY]=size(Truth);

Z=zeros(256,256);

for i=1:X
 for j=1:Y

p=Truth(i,j)+1;

Z(p,q)=Z(p,q)+I;

q=Result(i,j);

T=sum(max(Z)); Per=T/X/Y;

end

end

Ground Truth

1	1	1	2	2
1	1	1	2	2
3	3	4	4	4
3	3	4	4	4
3	3	4	4	4

Clustering Result

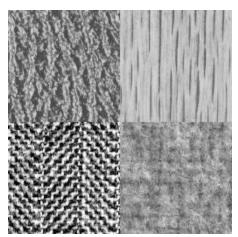
3	3	3	4	4
3	1	2	4	4
2	2	1	1	1
2	3	1	3	1
2	2	1	1	1

1	1	4	0
0	0	0	4
0	5	1	0
8	0	1	0

8 5 4 4

Sum=21

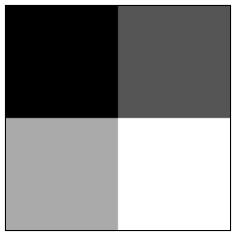
Texture Segmentation using K-mean and EM Algorithms (Mosaic A)



Mosaic A



K-mean clustering result



Ground truth segmentation

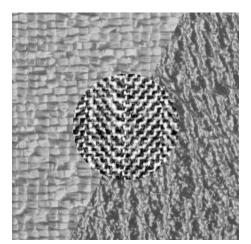


EM algorithm result Computer Vision

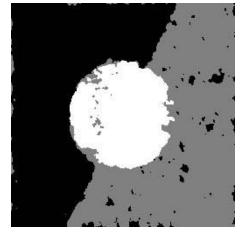
The 5-scales and 8-orientation Gabor filtering is used for texture feature extraction.

The dimension of feature vector is 5x8=40.

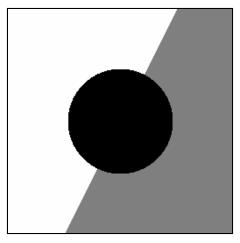
Texture Segmentation using K-mean and EM Algorithms (Mosaic B)



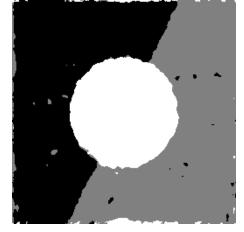
Mosaic B



K-mean clustering result



Ground truth segmentation



EM algorithm result **Computer Vision**

The 5-scales and 8-orientation Gabor filtering is used for texture feature extraction.

The dimension of feature vector is 5x8=40.





- Implement two clustering algorithms for image segmentation
 - For K-means, try to use a random method to find a good initialization.
 - Discuss the effect of initialization to each of them.
 - Compare different initializations for EM-based image segmentation.
- Some plots to show for each clustering
 - ▶ Plot the incomplete data likelihood $p(Y|\Theta)$ vs. the iteration number.
 - ▶ Plot the segmentation accuracy vs. the iteration number
- Additional requirements
 - Create a video to show the segmentation map for each iteration.
 - Find a couple of color images and add RGB (3-channel colors) or XY (pixel coordinates) feature along with Gabor features for segmentation. Discuss your findings.