

# Project 4: Image Segmentation Using K-means and EM

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Oklahoma State University

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## Project Objective

ECEN-5283 Computer Vision

#### Project Objective

#### **Objectives**

- Implement K-means and Expectation Maximization(EM) algorithms
- Apply them for image segmentation
- Analyze the result with different initialization
- Apply them on Gray and Colored image



#### K-means

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K-means

#### K-means clustering algorithm

- Start with initial guesses for cluster centers (centroids)
- For each data point, find closest cluster center (partitioning step)
- Replace each centroid by average of data points in its partition



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Experiment and Results

Analysis

Real World

Given a set of observations y into a K clusters.

$$\mathbf{x}_{i}^{(t)} = argmin_{i}\{y_{i} : \|y_{i} - \mu_{k}^{(t)}\|^{2} \ \forall_{k,i}, 1 \leq j \leq K, 1 \leq i \leq N\}$$

Afterwards, the center-points are repositioned by calculating the mean of the assigned observations to the respective center-points

$$\mu_k^{(t+1)} = \frac{1}{N_k} \sum_{x_i \in x_k^{(t)}} x_i$$

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 $y_i = (y_{i1},...y_{id})$ : If centroids are  $m_1, m_2,...m_k$ , and partitions are  $c_1, c_2,...c_k$ , then one can show that K-means converges to a local minimum of

$$\sum_{k=1}^K \sum_{i \in c_k} ||x_i - m_k||^2$$



## EM algorithm for Gaussian mixtures

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- EM can be thought of a probabilistic version of K-means
- Instead of hard assigning a data point to a cluster it assigns a probability
- The mean an covariance for Gaussian often initialized using fast K-means clustering
- EM is a two step algorithm

## EM algorithm

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E-Step:

$$\gamma(z_k) = p(z_k = 1|y) = \frac{p(y|z_k = 1)p(z_k = 1)}{p(y)}$$
$$= \frac{\alpha_k \mathcal{N}(y|\mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(y|\mu_j, \Sigma_j)}$$

M-step:

$$\mu_k = \frac{\sum_{n=1}^{N} \gamma(z_{nk}) y_n}{\sum_{n=1}^{N} \gamma(z_{nk})}$$
$$\Sigma_k = \frac{1}{N_k} \gamma_k(z_{nk}) (y_n - \mu_k) (y_n - \mu_k)^T$$



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The objective function for EM is

$$Inp(X|\alpha,\mu,\Sigma) = \sum_{n=1}^{N} In\{\sum_{k=1}^{K} \alpha_k \mathcal{N}(x_n|\mu_k,\Sigma_k)\}$$



## Test Image Mosaic A

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K-means

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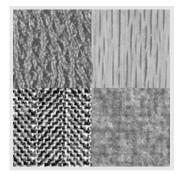


Figure: Test Image

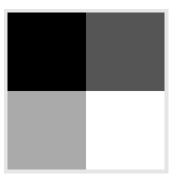


Figure: Ground Truth



#### K-means Initializations for A

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and Resi K-means

Analysi

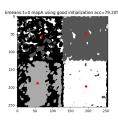


Figure: Good

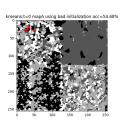


Figure: Bad



Figure: Random



## K-means Output for A

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K-means

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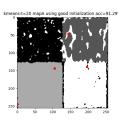


Figure: Good

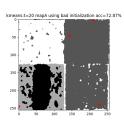


Figure: Bad



Figure: Random



#### K-means Performance for A

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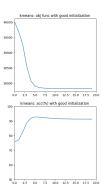
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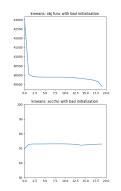
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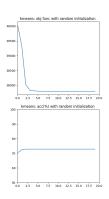


Figure: Good

Figure: Bad

Figure: Random



## Test Image Mosaic B

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Technical Background

K-means

Analysi

Real Worl

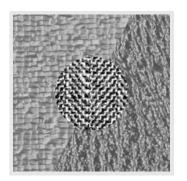


Figure: Test Image



Figure: Ground Truth



#### K-means Initializations for B

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Real World

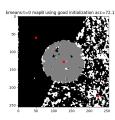


Figure: Good

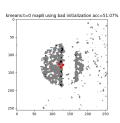


Figure: Bad



Figure: Random



## K-means Output for B

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K-means

EM

Analysi

Real World

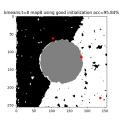


Figure: Good

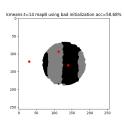


Figure: Bad



Figure: Random



#### K-means Performance for B

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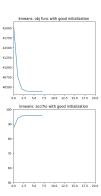
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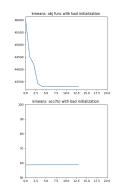
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Real World





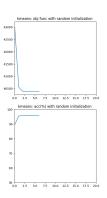


Figure: Good

Figure: Bad

Figure: Random



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N.B. EM initialized using the optimized output of the K-means. In this context, bad initialization for EM means the K-means was started with bad initialization and EM initialized with the output of that K-means



## EM Initializations by K-means for A

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Real World

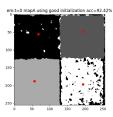


Figure: Good

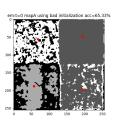


Figure: Bad



Figure: Random



## EM Output for A

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Real World

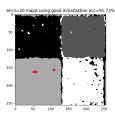


Figure: Good

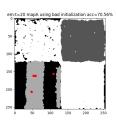


Figure: Bad



Figure: Random



#### EM Performance for A

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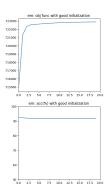
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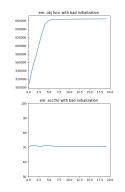
Project Objective

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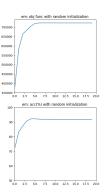


Figure: Good

Figure: Bad

Figure: Random



## **EM** Initialized by K-means for B

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Real World

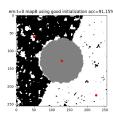


Figure: Good

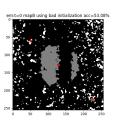


Figure: Bad



Figure: Random



## EM Output for B

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Technical Background

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Real World

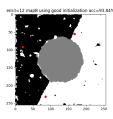


Figure: Good

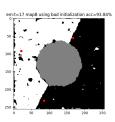


Figure: Bad



Figure: Random



#### EM Performance for B

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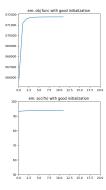
Project Objective

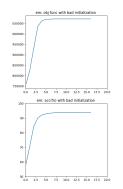
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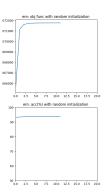


Figure: Good

Figure: Bad

Figure: Random



#### K-means Vs EM on A

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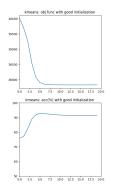
Project Objective

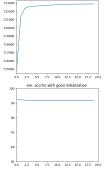
Technical Background

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Analysi

Real World





em: obi func with good initialization

Figure: K-means Good

Figure: EM Good



#### K-means Vs EM on B

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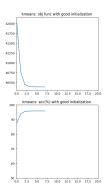
Project Objective

Technical Background

K-me

Analysi

Real World



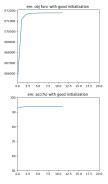


Figure: K-means Good

Figure: EM Good



#### K-means Vs EM on A

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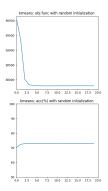
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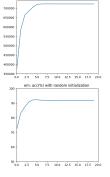
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Real World





em: obi func with random initialization

Figure: K-means Random

Figure: EM random



#### K-means Vs EM on B

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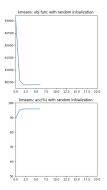
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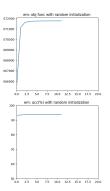


Figure: K-means Random

Figure: EM Random



## **Analysis**

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Analysis

- Experiments reaffirms the fact that both K-means and EM are sensitive to initialization; good initializations have better accuracy
- EM is more robust than K-means because in all cases it performs almost as good as K-means or much better than it.
- For example in random case K-means suffer 70% accuracy whereas EM has 90% accuracy
- The robustness is more visible in more complex segmentation for example in more complex real world image
- However K-means converges faster than EM



#### K-means on Real Image K=6

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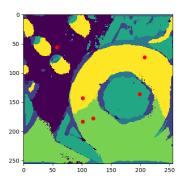
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Real World







## EM on Real Image

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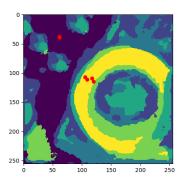
Technical Background

Background Experiment

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Real World







#### K-means on Real Image K=4

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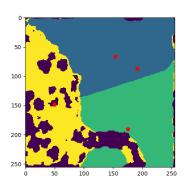
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view of Boomer Lake. K means is confused by Google's watermark. It also did not segmented the bank.



## EM on Real Image

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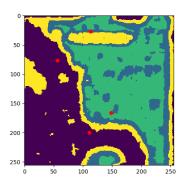
Technical Background

Experimen

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Real World





segmented the watermark in a different cluster. Also segmented the lake, land, bank and trees.