

EE4212 Computer Vision

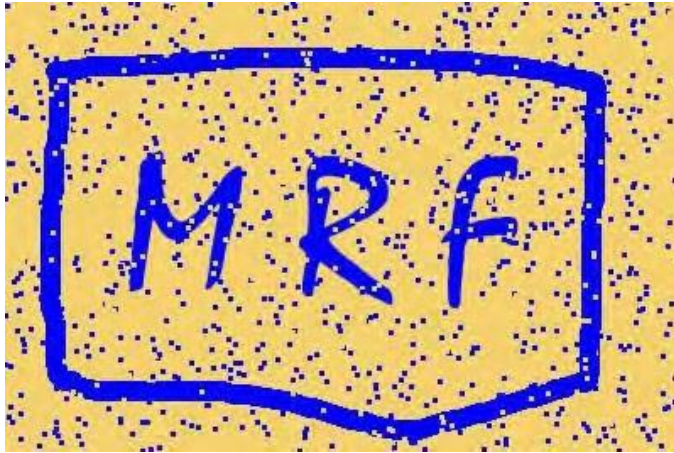
Assignment 2: Markov Random Field and Graphcuts

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Part 1 : Noise Cleaning

Remove pepper noise in MRF image below using binary graphcuts.



The code part1.m implements this algorithm. The results for different m_lambda are shown below.

$m_lambda = 16$



$m_lambda = 20$



m_lambda = 25



m_lambda = 30 (Best result)



m_lambda = 35



m_lambda = 40



The best m_lambda value lies between 30 and 35 without treating the blue colour MRF and the outline. A good result can be considered as m_lambda = 30 as shown above.

Part 2: Colour Segmentation

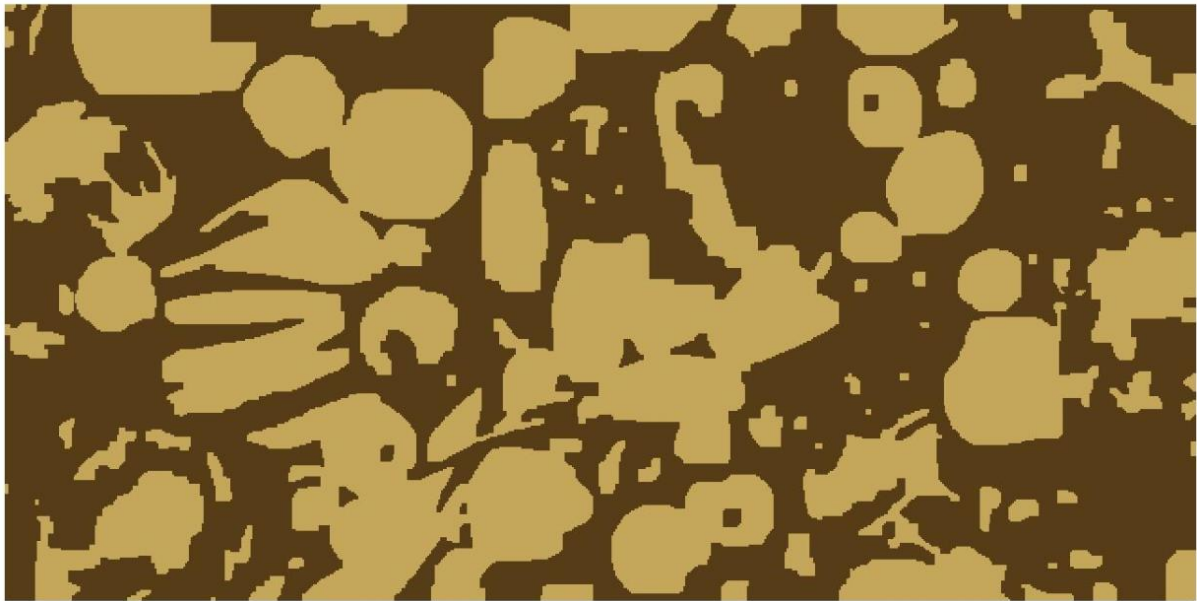
The code part2.m implements K-means clustering to obtain k number of segmented colours followed by building covariance matrix.

The results are shown below.

Original image



Segmentation results for $k = 2$



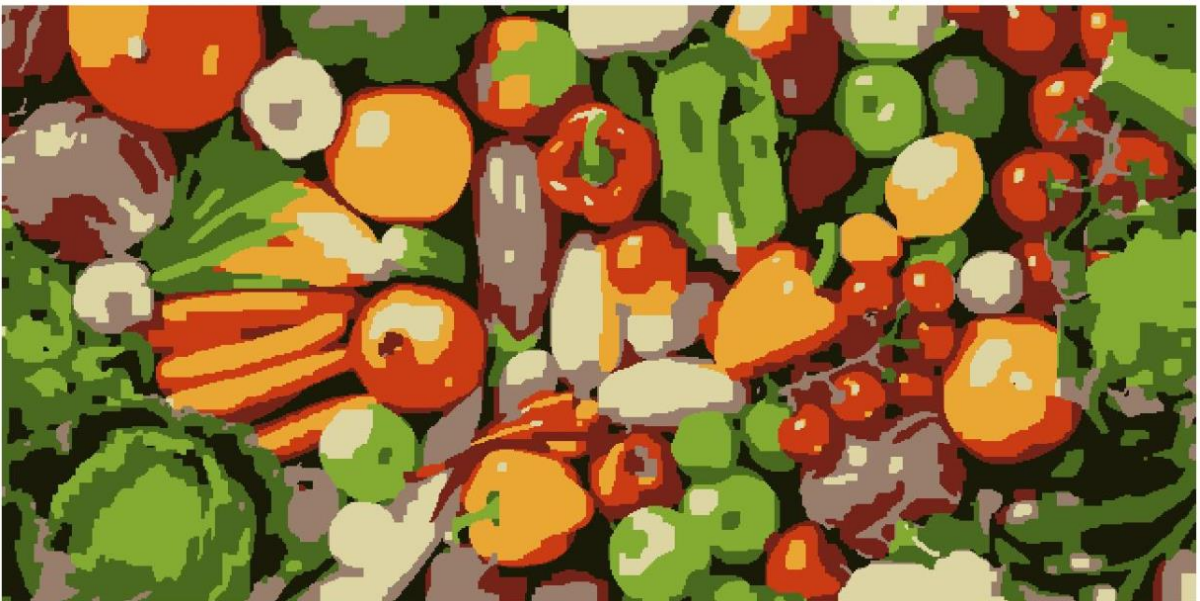
Segmentation results for $k = 3$



Segmentation results for $k = 4$



Segmentation results for $k = 8$



Segmentation results for $k = 15$



Segmentation results for $k = 25$



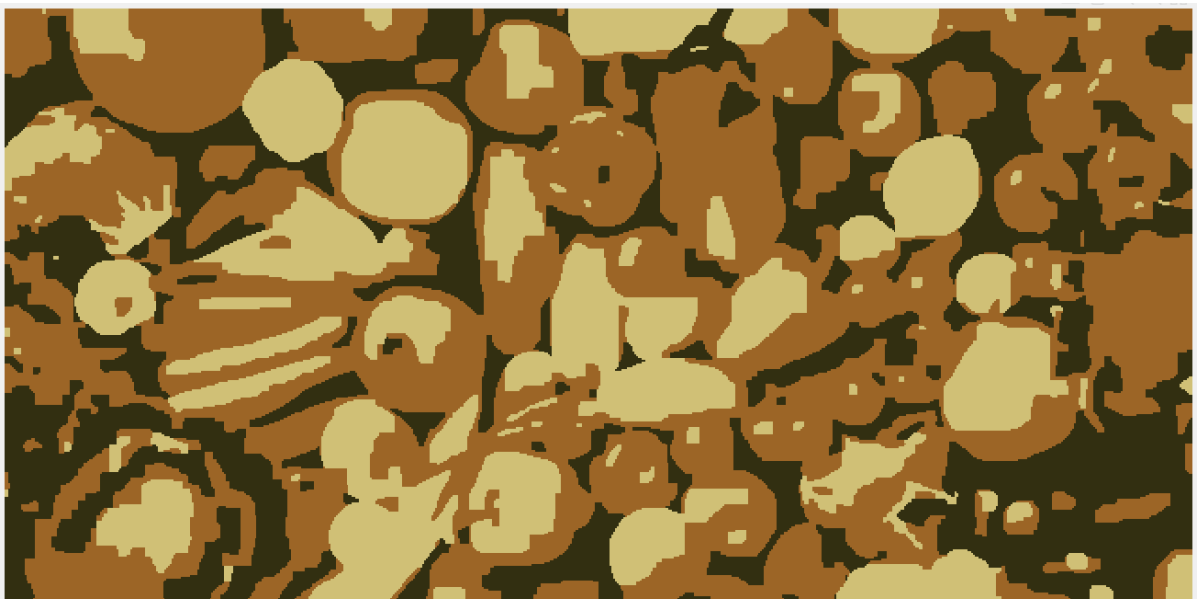
Drawbacks of the algorithm

- 1) Time consumption is high as the k centers become larger even though sparse matrix was used. The problem is computationally difficult (NP-hard);
- 2) K-means can converge to a “local minimum” not always the global minimum. It only detects spherical clusters only.
- 3) The problem with K-means clustering is that it is highly sensitive to initial choice of random k center points. For example, $k_clusters = 3$ when run twice gives a slightly different result as shown by red circles below. It is also sensitive to outliers.

Run 1



Run 2



- 4) Even with efficient graph cuts, an MRF formulation has too many nodes for interactive results.

Suggestions to improve the algorithm

- 1) Use alpha-expansion moves to speed up.
- 2) Use mean-shift which is Model-free, does not assume any prior shape (spherical etc.) on data clusters. It is just a single parameter (window size h). h has a physical meaning (unlike k-means). It finds variable number of modes and it is robust to outliers
- 2) We can use K-means++ algorithm to prevent arbitrarily bad local minima because it picks new centers with probability proportional to SSD of pixels.
- 4) We can use tricks like Superpixels to group together similar-looking pixels for efficiency of further processing. It is computationally cheap, local oversegmentation.

Appendix

Segmentation results for $k = 3$



Segmentation results for $k = 12$



Segmentation results for $k = 12$



Segmentation results for $k = 12$



Segmentation results for $k = 12$



Segmentation results for $k = 12$

