Report

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Introduction to GRAB CUT:

This process makes use of the graph structure used in graph cut algorithm. Each node in the graph represents a pixel of the image. Each node is connected to its neighbouring pixels and also to a background and foreground node. On applying min-cut on the above graph, the nodes connected to the foreground node represents pixels in the foreground and similarly nodes connected to the background node represents background pixels.

Algorithm :-

0.) Initial guess of the foreground and background pixels as everything inside bounding box is considered as a foreground and outside of the bounding box is considered as background where the bounding box is supplied by the user

1.)A source and sink node are added representing foreground and background.

2.)Two types of edge weights are set(Unary and Binary).

3.)Assign weights to edges as follows:-

i.)Binary weights = c*exp(-b*(diff between intensities of pixels)^2)

ii.)Unary weights = -log(probability of a pixel belonging to the GMM)

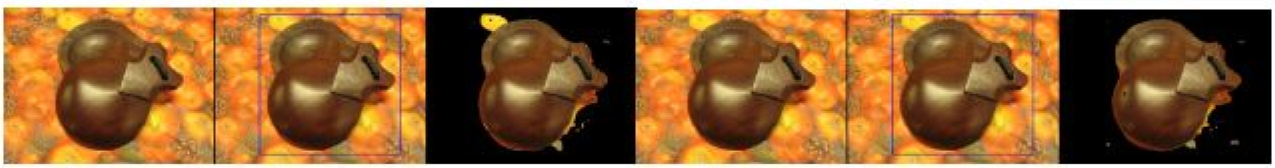
4.)Repeat this N times.

Experiments :-

1 . The choice of gamma.

Gamma = 5

Gamma = 50



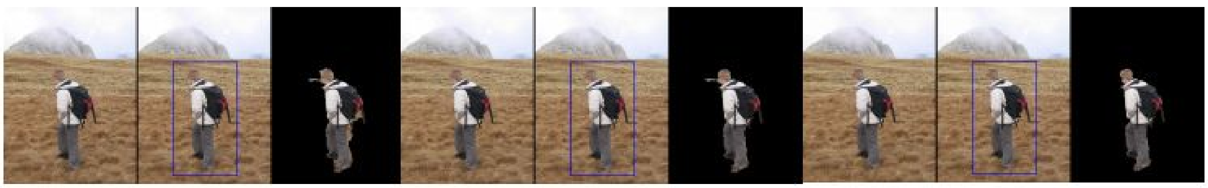
Gamma = 100

- The choice of gamma affects the smoothness term of the energy equation.
- A low value of gamma can prevent the equation from penalising different neighbouring color intensities and
- A higher value of gamma can cause the penalisation to not flip correctly.
- As can be seen from the results, higher value of gamma penalises the difference in neighbouring pixels of different intensities much more than a smaller value of gamma. Moreover, the data term becomes more confident and corrective when we give a high value of gamma.

2 . The number of mixture components in the GMM

K = 5

K = 10



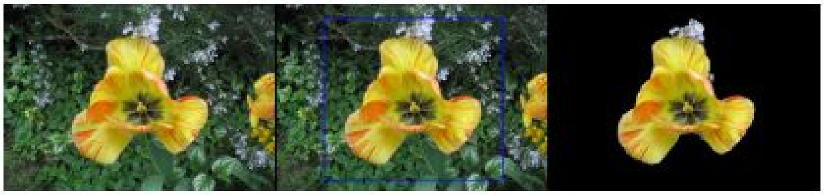
K = 15

K = 20

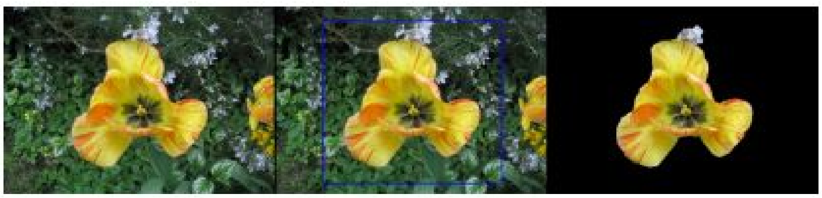
As the number of components increase, it becomes harder for the GMM to learn the distinct separation between the foreground and the background colors. This is because there will be an overlap between the foreground and the background color components. However, when there are extremely small numbers of components, it becomes harder to represent all the colors in the foreground and the background. It is empirically seen that GMMs with K=5 components works the best for the various images.

3. The number of iterations of GMM updating and energy minimisation

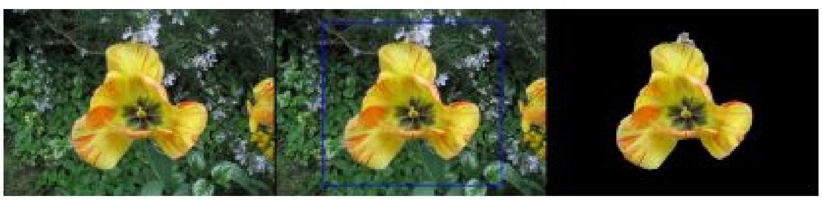
1 Iteration



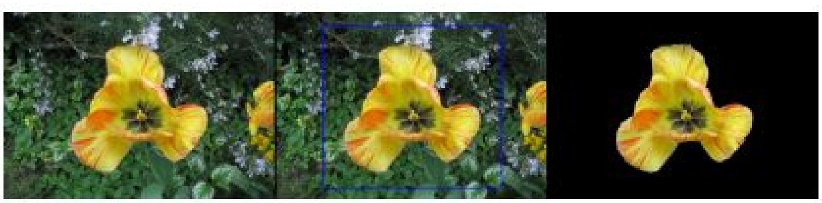
2 Iteration



3 Iteration



4 Iteration



As the number of iterations increases, the energy minimisation better estimates the foreground background cut and separation. With every iteration, we estimate the foreground and background colors and assign them to the GMM. Then the GMM components learn the separation better in the next step of the iteration, hence, increasing the confidence and accuracy in the graph st-mincut and hence the segmentation.