

Assignment 3 - Image Segmentation using MRFs

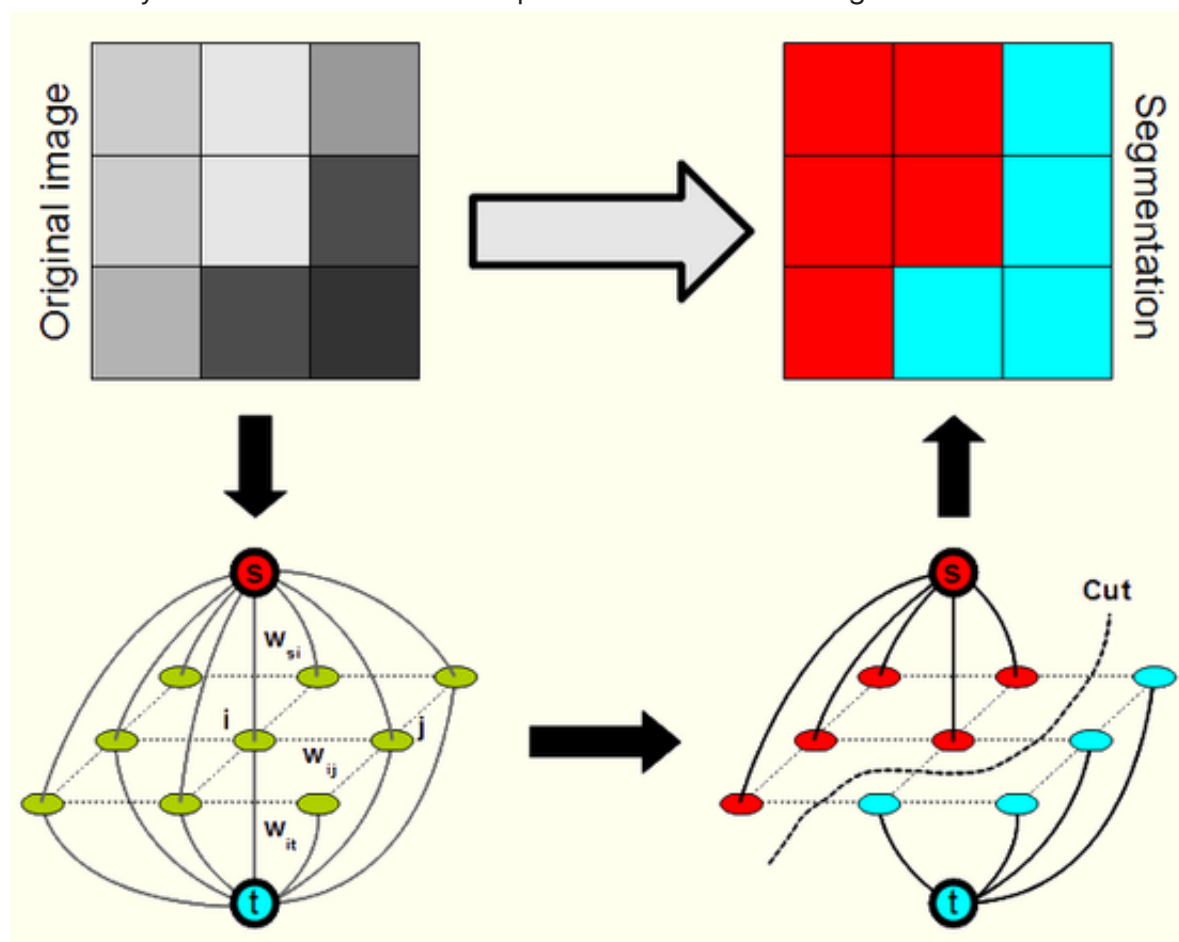
GrabCut

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For this assignment you will implement the GrabCut method mentioned in this [paper](#). It is essentially an iterative version of GraphCut as shown in the figure below.



The code below takes an input image and follows these steps:

- It requires a bounding box to be drawn by the user to roughly segment out the foreground pixels
- It runs an initial min-cut optimization using the provided annotation
- The result of this optimization gives an initial segmentation
- To further refine this segmentation, the user provides two kinds of strokes to aid the optimization
 - strokes on the background pixels

- strokes on the foreground pixels
- The algorithm now utilizes this to refine the original segmentation

You are allowed to use standard GMM libraries for the implementation. For usage of other libraries, please contact the TAs.

You can view this [video](#) to get a better idea of the steps involved.

Image segmentation is one exciting application of MRFs. You can further read about other applications of MRFs for Computer Vision [here](#).

Useful Links

- https://courses.engr.illinois.edu/cs543/sp2011/lectures/Lecture%2012%20-%20MRFs%20and%20Graph%20Cut%20Segmentation%20-%20Vision_Spring2011.pdf

In [1]:

```
import numpy as np
import cv2
import matplotlib.pyplot as plt
```

In [2]:

```
class EventHandler:
    """
    Class for handling user input during segmentation iterations
    """

    def __init__(self, flags, img, _mask, colors):

        self.FLAGS = flags
        self.ix = -1
        self.iy = -1
        self.img = img
        self.img2 = self.img.copy()
        self._mask = _mask
        self.COLORS = colors

    @property
    def image(self):
        return self.img

    @image.setter
    def image(self, img):
        self.img = img

    @property
    def mask(self):
        return self._mask

    @mask.setter
    def mask(self, _mask):
        self._mask = _mask

    @property
    def flags(self):
        return self.FLAGS
```

```

@flags.setter
def flags(self, flags):
    self.FLAGS = flags

def handler(self, event, x, y, flags, param):

    # Draw the rectangle first
    if event == cv2.EVENT_RBUTTONDOWN:

        self.FLAGS['DRAW_RECT'] = True
        self.ix, self.iy = x,y

    elif event == cv2.EVENT_MOUSEMOVE:

        if self.FLAGS['DRAW_RECT'] == True:

            self.img = self.img2.copy()
            cv2.rectangle(self.img, (self.ix, self.iy), (x, y), self.COLORS['DRAW_RECT'])
            # cv2.rectangle(self._mask, (self.ix, self.iy), (x, y), self.COLORS['DRAW_RECT'])
            self.FLAGS['RECT'] = (min(self.ix, x), min(self.iy, y), abs(self.ix - x), abs(self.iy - y))
            self.FLAGS['rect_or_mask'] = 0

        elif event == cv2.EVENT_RBUTTONUP:

            self.FLAGS['DRAW_RECT'] = False
            self.FLAGS['rect_over'] = True
            cv2.rectangle(self.img, (self.ix, self.iy), (x, y), self.COLORS['DRAW_RECT'])
            cv2.rectangle(self._mask, (self.ix, self.iy), (x, y), 127, -1)
            self.FLAGS['RECT'] = (min(self.ix, x), min(self.iy, y), abs(self.ix - x), abs(self.iy - y))
            self.FLAGS['rect_or_mask'] = 0

    # Draw strokes for refinement

    if event == cv2.EVENT_LBUTTONDOWN:
        if self.FLAGS['rect_over'] == False:
            print('Draw the rectangle first.')
        else:
            self.FLAGS['DRAW_STROKE'] = True
            cv2.circle(self.img, (x,y), 6, self.FLAGS['value']['color'], 2)
            cv2.circle(self._mask, (x,y), 6, self.FLAGS['value']['value'], 2)

    elif event == cv2.EVENT_MOUSEMOVE:
        if self.FLAGS['DRAW_STROKE'] == True:
            cv2.circle(self.img, (x, y), 6, self.FLAGS['value']['color'], 2)
            cv2.circle(self._mask, (x, y), 6, self.FLAGS['value']['value'], 2)

    elif event == cv2.EVENT_LBUTTONUP:
        if self.FLAGS['DRAW_STROKE'] == True:
            self.FLAGS['DRAW_STROKE'] = False
            cv2.circle(self.img, (x, y), 3, self.FLAGS['value']['color'], 2)
            cv2.circle(self._mask, (x, y), 3, self.FLAGS['value']['value'], 2)

```

In [6]:

```

from sklearn.mixture import GaussianMixture

class GMM(object):

    def __init__(self, samples, K):

```

```

assert len(samples) > K, "No samples or not enough samples found"
assert K > 0, "KMeans must have atleast 1 component"

self.K = K
self.samples = samples.reshape(-1,3)
self.weights = np.array([1/self.K for i in range(self.K)])

self.model = GaussianMixture(
    n_components=self.K, covariance_type="full",
    weights_init=self.weights, n_init = 2
).fit(samples)

self.means = self.model.means_
self.covs = self.model.covariances_

self.predictions = self.model.predict(samples)

def update_model(self, samples):

    self.samples = samples.reshape(-1,3)
    self.predictions = self.model.predict(self.samples)

    for i in range(self.K):

        F = self.samples[self.predictions == i]

        if len(F) < 2:
            self.weights[i] = 0
            for j in range(self.K):
                if j == i:
                    continue
                if self.weights[j] > 1e-2:
                    self.weights[j] -= 1e-2
                    self.weights[i] += 1e-2
                break
            continue

        ni = len(F)
        self.weights[i] = ni/len(self.samples)
        if self.weights[i] == 0.:
            for j in range(self.K):
                if j == i:
                    continue
                if self.weights[j] > 1e-2:
                    self.weights[j] -= 1e-2
                    self.weights[i] += 1e-2
                break

        self.means[i] = F.mean(axis=0)
        self.covs[i] = np.cov(F.T).T

    for i in range(self.K):
        while np.linalg.det(self.covs[i]) == 0:
            self.covs[i][0,0] += 0.001
            self.covs[i][1,1] += 0.001
            self.covs[i][2,2] += 0.001

    try:
        self.model = GaussianMixture(
            n_components=self.K, covariance_type="full",
            means_init=self.means, precisions_init=self.covs,

```

```

        weights_init=self.weights, n_init =
    ).fit(samples)
except:
    self.model = GaussianMixture(
        n_components=self.K, covariance_type='full',
        n_init = 1
    ).fit(samples)

    self.predictions = self.model.predict(self.samples)

    for i in range(self.K):
        F = self.samples[self.predictions == i]

        if len(F) < 2:
            self.weights[i] = 0
            continue

        ni = len(F)
        self.weights[i] = ni/len(self.samples)

    self.means = self.model.means_
    self.covs = self.model.covariances_

    self.predictions = self.model.predict(self.samples)

def prob(self, i, samples):

    samples = samples.reshape(-1,3)

    assert i < self.K, "Exceeded number of components"
    mu, cov = self.means[i], self.covs[i]

    mu = mu.reshape(-1,3)

    fac = []
    for j in samples:
        fac += [(j - mu) @ np.linalg.pinv(cov) @ (j - mu).T]
    fac = np.array(fac).reshape(-1,1)

    return (1/np.sqrt(2*np.linalg.det(cov))) * np.exp(-0.5*fac)

def calculate_U(self, samples):

    samples = samples.reshape(-1,3)
    return -self.model.score_samples(samples).reshape(-1,1)

```

In [13]:

```

import igraph as ig

class GrabCut(object):

    def __init__(self, img, mask, K=5, n_iters=5, gamma=50):

        print("Initializing...")

        self.h = img.shape[0]
        self.w = img.shape[1]

        img = img.astype('float32')
        self.original_img = img.copy()

```

```

self.img = img.reshape(-1,3)
self.mask = mask.reshape(-1)

# Initializing parameters
self.K = K
self.n_iters = n_iters
self.gamma = gamma
self.lamda = 1
self.calc_beta()

# Initializing Graph
self.s = self.h*self.w
self.t = self.h*self.w + 1
self.calculate_V()

# Initializing GMMs
self.gm_fg = GMM(self.img[(self.mask == 1) + (self.mask == 2)], self.K)
self.gm_bg = GMM(self.img[self.mask == 0], self.K)

# Finding trimap pixels
self.probable_fg = self.img[self.mask == 2]
self.fg = self.img[self.mask == 1]
self.bg = self.img[self.mask == 0]

# Getting indices of trimap pixels
self.probable_indices = (np.where(self.mask == 2))[0]
self.fg_indices = (np.where(self.mask == 1))[0]
self.bg_indices = (np.where(self.mask == 0))[0]

# Initializing alphas
self.alphas = np.zeros(self.h*self.w)
self.alphas[(self.mask == 1) | (self.mask == 2)] = 1

def calc_beta(self):

    # Gets differences between pixels in the required directions
    self.l = (self.original_img[:, 1:] - self.original_img[:, :-1])**2
    self.u = (self.original_img[1:, :] - self.original_img[:-1, :])**2
    self.ur = (self.original_img[1:, :-1] - self.original_img[:-1, 1:])**2
    self.ul = (self.original_img[1:, 1:] - self.original_img[:-1, :-1])**2

    # Uses the formula for beta
    self.beta = np.sum(self.l) + np.sum(self.u) + \
                np.sum(self.ur) + np.sum(self.ul)
    self.beta = (4*self.h*self.w - 3*(self.w + self.h) + 2)/(2*self.beta)

def calculate_V(self):

    # Calculates the V term to add to the graph's edges capacity
    cap_l = self.gamma*np.exp(-self.beta*np.sum(self.l, axis=2))
    cap_u = self.gamma*np.exp(-self.beta*np.sum(self.u, axis=2))
    cap_ul = self.gamma*np.exp(-self.beta*np.sum(self.ul, axis=2))
    cap_ur = self.gamma*np.exp(-self.beta*np.sum(self.ur, axis=2))

    # Dividing by distance for diagonal terms
    cap_ul/=np.sqrt(2)
    cap_ur/=np.sqrt(2)

    # Initializing variables
    self.edges_V = []
    self.capacity_V = []

```

```

l_edges = []
u_edges = []
ul_edges = []
ur_edges = []

# Adds the edges in the required directions
for i in range(self.h):
    for j in range(self.w):
        curr = i*self.w+j
        if i:
            u_edges += [((i-1)*self.w+j, curr)]
        if j:
            l_edges += [(i*self.w+j-1, curr)]
        if i and j:
            ul_edges += [((i-1)*self.w+j-1, curr)]
        if i and j+1 < self.w:
            ur_edges += [((i-1)*self.w+j+1, curr)]

# Updates edges and capacities
self.edges_V = l_edges + u_edges + ul_edges + ur_edges
self.capacity_V += cap_l.ravel().tolist() + \
                    cap_u.ravel().tolist() + \
                    cap_ul.ravel().tolist() + \
                    cap_ur.ravel().tolist()

def reclassify_img(self):

    self.fg = self.img[self.alphas == 1]
    self.bg = self.img[self.alphas == 0]

def create_graph(self):

    self.graph = ig.Graph(self.h * self.w + 2)

    edges = []
    self.capacity = []

    # getting already created n-links
    edges = self.edges_V.copy()
    self.capacity = self.capacity_V.copy()

    # creating t-links
    U_pr_bg = self.gm_bg.calculate_U(self.probable_fg).reshape(-1)
    U_pr_fg = self.gm_fg.calculate_U(self.probable_fg).reshape(-1)

    for u in self.probable_indices:
        edges += [(self.s, u)]
    for u in self.probable_indices:
        edges += [(self.t, u)]

    self.capacity += (self.lamda*U_pr_bg.ravel()).tolist()
    self.capacity += (self.lamda*U_pr_fg.ravel()).tolist()

    for i in self.fg_indices:
        edges += [(self.s, i), (self.t, i)]
        self.capacity += [20*self.gamma, 0]

    for i in self.bg_indices:
        edges += [(self.s, i), (self.t, i)]
        self.capacity += [0, 20*self.gamma]

```

```

        self.graph.add_edges(edges)

    def find_mincut(self):

        mincut = self.graph.st_mincut(self.s, self.t, self.capacity)

        self.alphas = np.zeros((self.h*self.w + 2))
        self.alphas[np.array(mincut.partition[0])] = 1
        self.alphas = self.alphas[:-2].reshape(self.h, self.w)

        img2 = self.img.copy().reshape(self.h, self.w, 3)
        img2[self.alphas == 0] = 0
        # plt.imshow(img2[:,:,:-1])
        # plt.show()

        self.alphas = self.alphas.reshape(self.h*self.w)

    def run_grabcut(self):

        for i in range(self.n_iters):

            print(f"\nIteration {i+1}")
            self.reclassify_img()

            print("Updating model...")
            self.gm_fg.update_model(self.fg)
            self.gm_bg.update_model(self.bg)

            print("Creating graph..")
            self.create_graph()

            print("Finding mincut..")
            self.find_mincut()

            # Returning the final mask
            self.alphas[self.alphas == 1] = 255
            self.alphas = self.alphas.reshape(self.h, self.w)
            return self.alphas.astype('uint8')

```

In [47]:

```

def run(filename: str):
    """
    Main loop that implements GrabCut.

    Input
    -----
    filename (str) : Path to image
    """

    COLORS = {
        'BLACK' : [0,0,0],
        'RED'   : [0, 0, 255],
        'GREEN' : [0, 255, 0],
        'BLUE'  : [255, 0, 0],
        'WHITE' : [255,255,255]
    }

    DRAW_BG = {'color' : COLORS['BLACK'], 'val' : 0}
    DRAW_FG = {'color' : COLORS['WHITE'], 'val' : 1}

```



```

FLAGS = {
    'RECT' : (0, 0, 1, 1),
    'DRAW_STROKE': False,           # flag for drawing strokes
    'DRAW_RECT' : False,           # flag for drawing rectangle
    'rect_over' : False,           # flag to check if rectangle is drawn
    'rect_or_mask' : -1,           # flag for selecting rectangle or stroke
    'value' : DRAW_FG,             # drawing strokes initialized to mask
}

img = cv2.imread(filename)
h,w = img.shape[:2]
# h/=2
# w/=2
# img = cv2.resize(img, (int(w), int(h)))
img2 = img.copy()
mask = np.zeros(img.shape[:2], dtype = np.uint8) # mask is a binary array
#
output = np.zeros(img.shape, np.uint8)           # output image to be saved

# Input and segmentation windows
cv2.namedWindow('Input Image')
cv2.namedWindow('Segmented output')

EventObj = EventHandler(FLAGS, img, mask, COLORS)
cv2.setMouseCallback('Input Image', EventObj.handler)
cv2.moveWindow('Input Image', img.shape[1] + 10, 90)

while(1):

    img = EventObj.image
    mask = EventObj.mask
    FLAGS = EventObj.flags
    cv2.imshow('Segmented image', output)
    cv2.imshow('Input Image', img)

    k = cv2.waitKey(1)

    # key bindings
    if k == 27:
        # esc to exit
        break

    elif k == ord('0'):
        # Strokes for background
        FLAGS['value'] = DRAW_BG

    elif k == ord('1'):
        # FG drawing
        FLAGS['value'] = DRAW_FG

    elif k == ord('r'):
        # reset everything
        FLAGS['RECT'] = (0, 0, 1, 1)
        FLAGS['DRAW_STROKE'] = False
        FLAGS['DRAW_RECT'] = False
        FLAGS['rect_or_mask'] = -1
        FLAGS['rect_over'] = False
        FLAGS['value'] = DRAW_FG
        img = img2.copy()
        mask = np.zeros(img.shape[:2], dtype = np.uint8)

```

```

        EventObj.image = img
        EventObj.mask = mask
        output = np.zeros(img.shape, np.uint8)

    elif k == 13:
        # Press carriage return to initiate segmentation

        #-----#
        # Implement GrabCut here.                                #
        # Function should return a mask which can be used #
        # to segment the original image as shown on L90      #
        #-----#

        EventObj.flags = FLAGS
        mask = EventObj.mask
        mask[mask==255] = 1
        mask[mask==127] = 2

        if np.sum(mask) == 0:
            print("Please reselect points")
            continue

        grabcut_obj = GrabCut(img2, mask, 5, 3)
        mask2 = grabcut_obj.run_grabcut()
        output = cv2.bitwise_and(img2, img2, mask=mask2)

#         To reuse resultant mask
#         mask = mask2
#         mask[mask==255] = 1

    elif k == ord('q'):
        break

    # uncomment to save outputs (will overwrite existing)
#     plt.imsave(f"../images/outputs/study_output_{filename.split('/')[2]}")
#     plt.imsave(f"../images/outputs/study_input_{filename.split('/')[2]}")

```

In [50]:

```

if __name__ == '__main__':
    filename = '../images/person8.jpg' # Path to image file
    run(filename)
    cv2.destroyAllWindows()

```

Initializing...

Iteration 1
 Updating model...
 Creating graph..
 Finding mincut..

Iteration 2
 Updating model...
 Creating graph..
 Finding mincut..

Iteration 3
 Updating model...
 Creating graph..
 Finding mincut..

Report

Contents

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Introduction

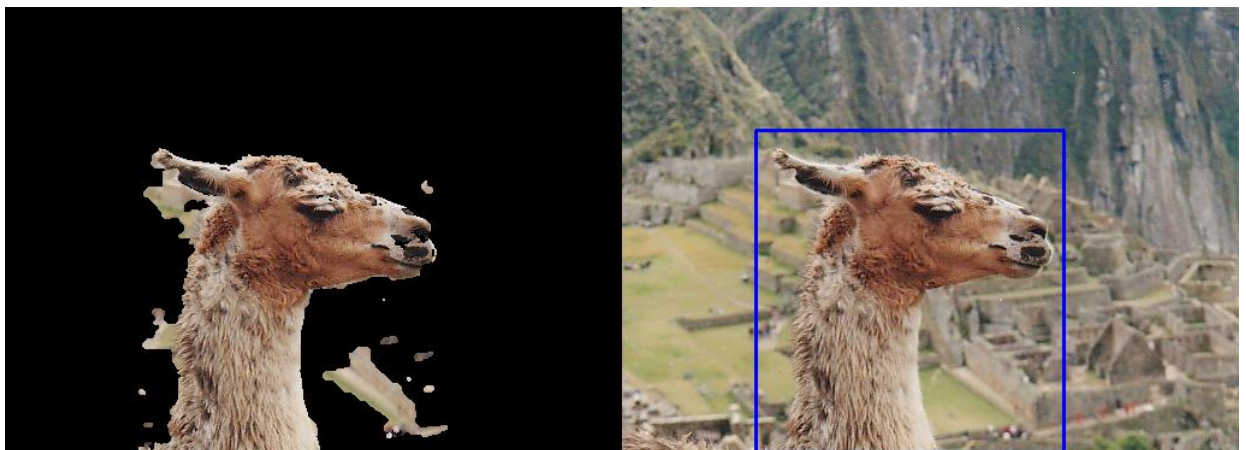
The GrabCut algorithm works robustly and gives a good output on almost all the images with the parameters mentioned in the paper, ie.

- $\gamma = 50$
 - $\lambda = 9\gamma$
 - GMM Components = 5
 - Iterations = 3
-

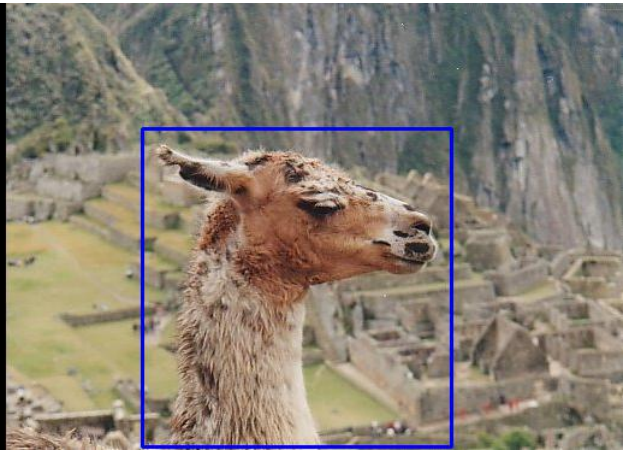
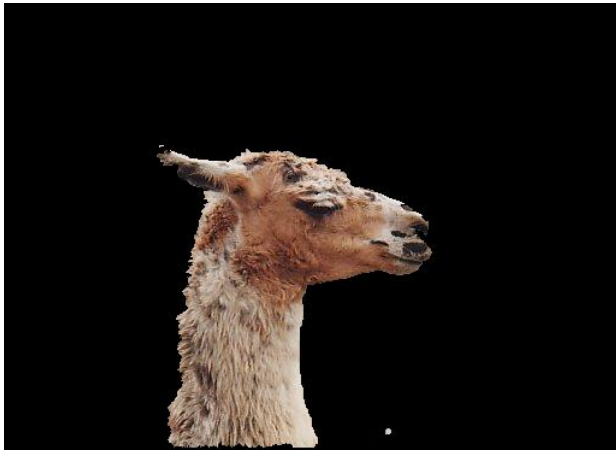
Study of the Effect of Changing Parameters

1. Varying γ

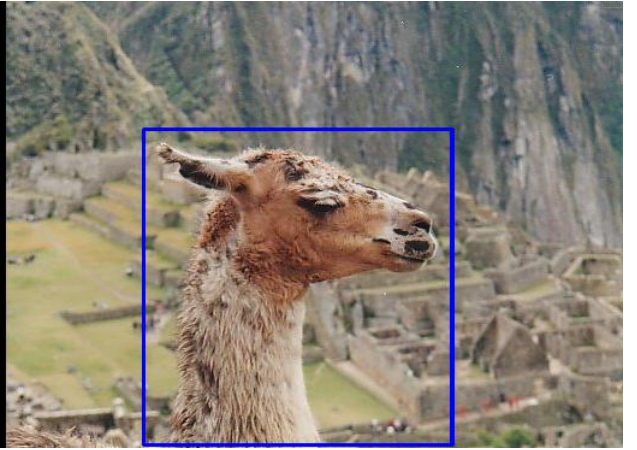
$$\gamma = 2$$



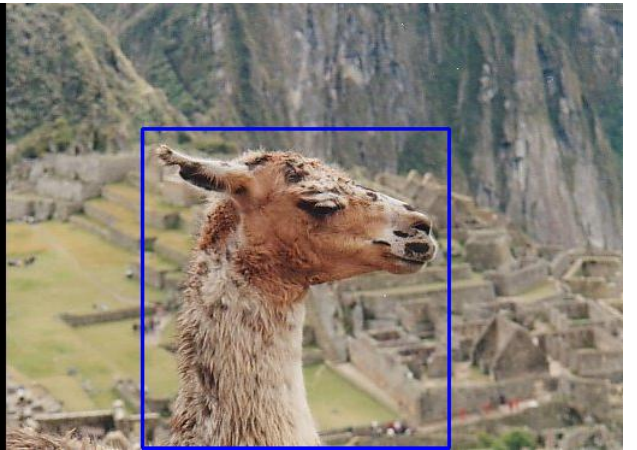
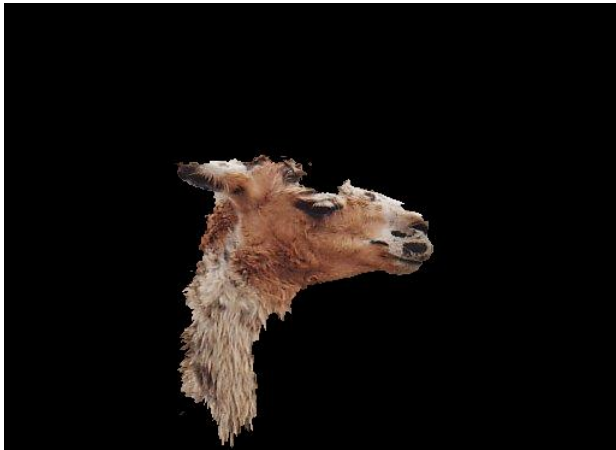
$$\gamma = 20$$



$\gamma = 50$



$\gamma = 200$



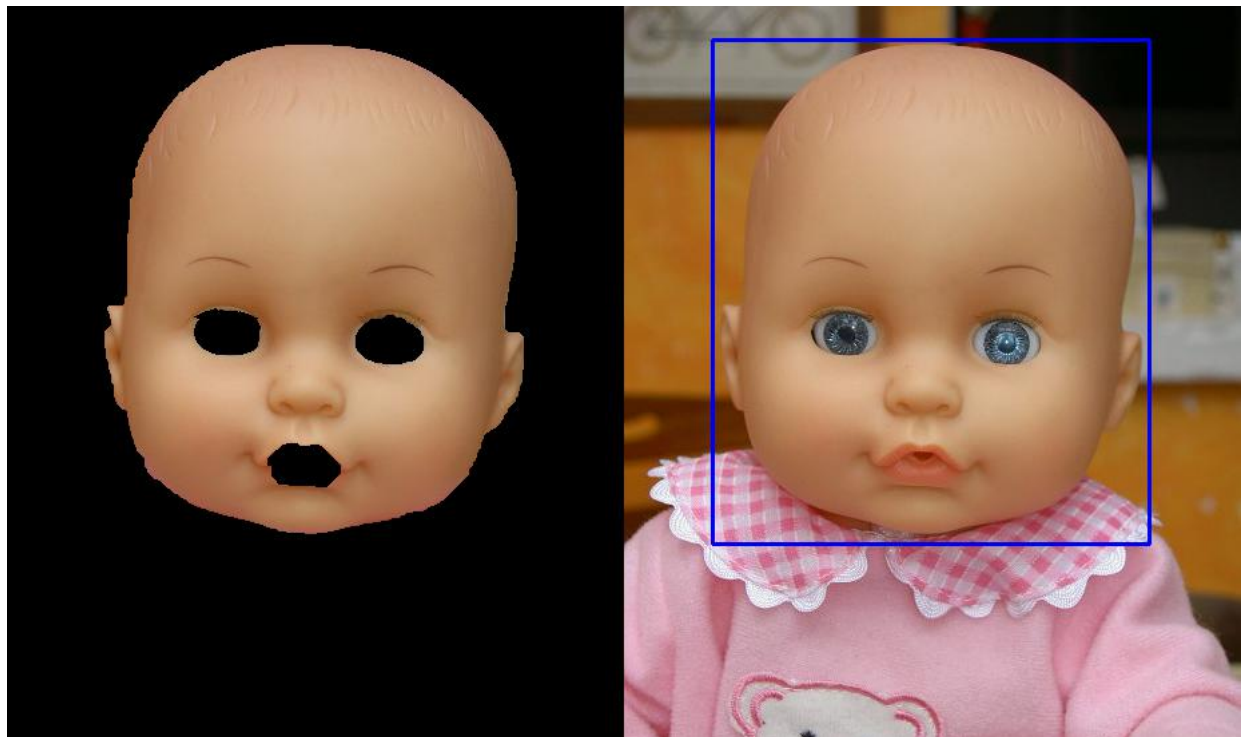
Inference

As we can see, increasing γ makes the segmentation smoother. This is because it increases the cost of removing the links between neighboring pixels, thus forcing the algorithm to assign nearby pixels the same label unless there's a big difference in the intensities of the nearby pixel.

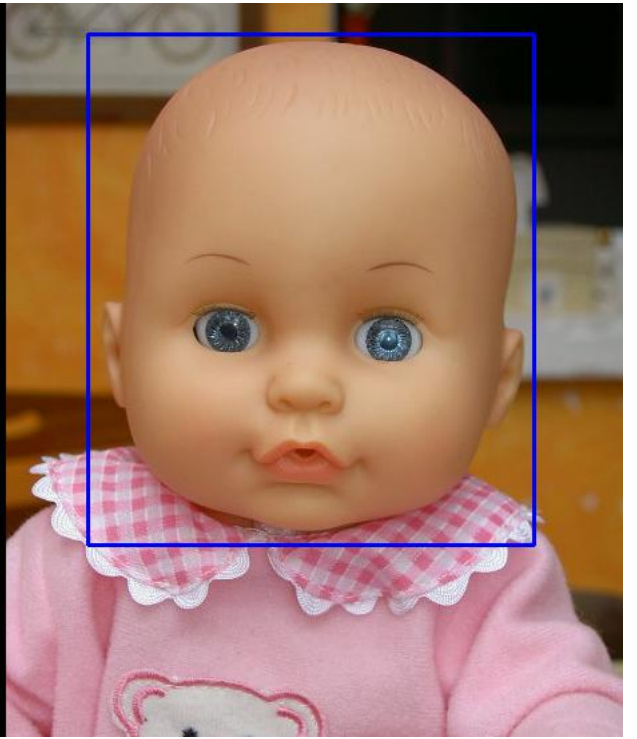
With a lower value of γ , this inter-pixel weight is low and hence there is more "noise" in the sense that there are many areas where nearby pixels are assigned opposite labels creating 'islands' of wrongly marked foregrounds. With extremely high values of γ , this inter pixel weight is extremely high, erasing useful parts of the foreground too. At moderate values of γ (eg. 50), the inter pixel weights are perfectly balanced with respect to the unary weights, giving a good segmentation.

2. Varying No. of GMM Components

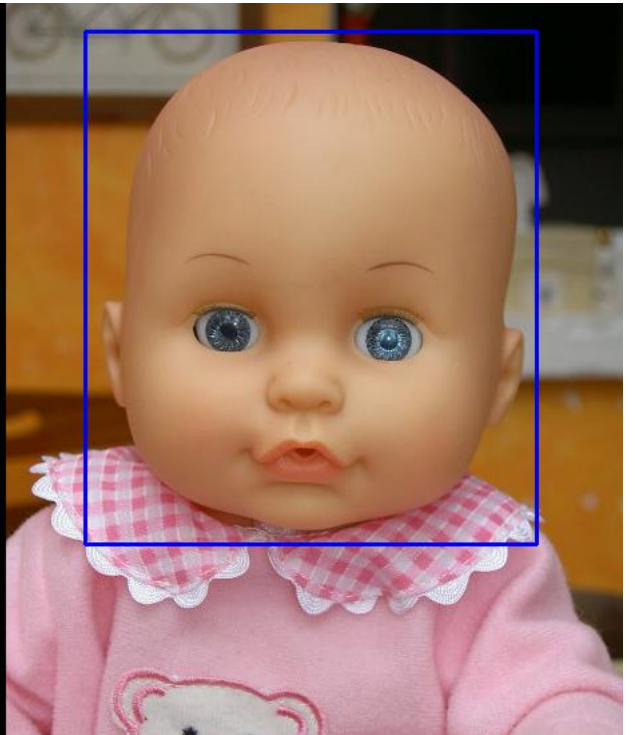
$K = 1$



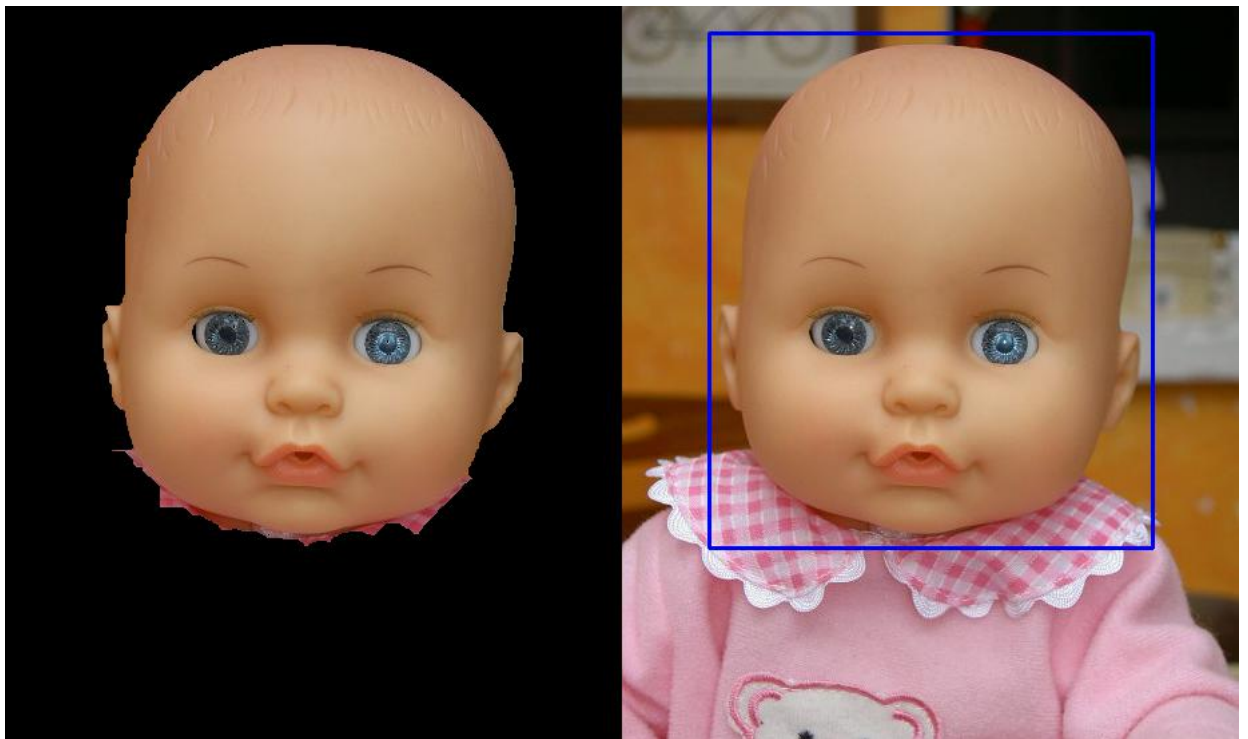
$K = 3$



$K = 5$



$K = 20$



Inference

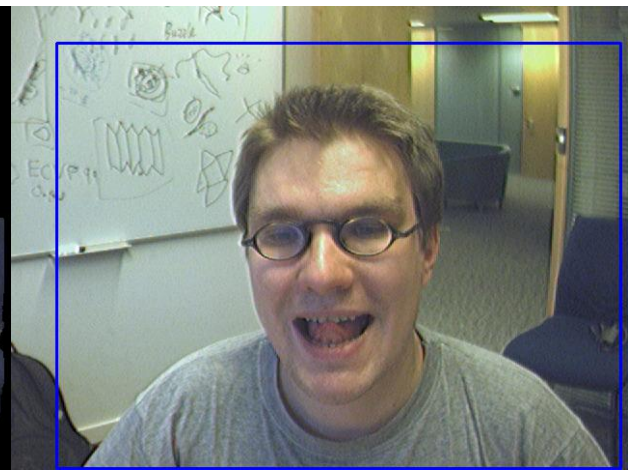
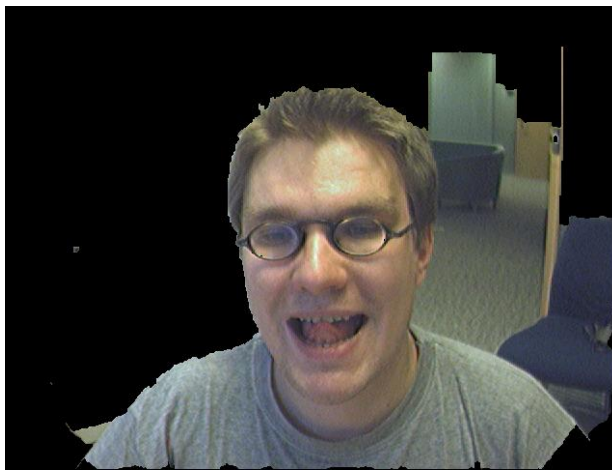
From the above results, we see that increasing the number of components gives the algorithm greater flexibility while marking FG and BG, and hence the results are better and more detailed as we increase the number of components.

At $K = 1$, we can see that since GrabCut can choose only one mean and covariance to model the FG and BG, it may not be able to effectively capture the entire marked BG or probably FG region. Hence in this case, we can see that the eyes and mouth although being FG, are marked as BG. This demonstrates how the single component GMM is not able to capture the different colors and intensities of the eyes and mouth as it is more tuned towards the skin (as it is the most present).

For higher K's, we consistently get good segmentation results, with the tradeoff being the time taken to run. Initializing a GMM with higher number of components takes longer than that with a lesser number of components.

3. Varying the Fit of the Bounding Box

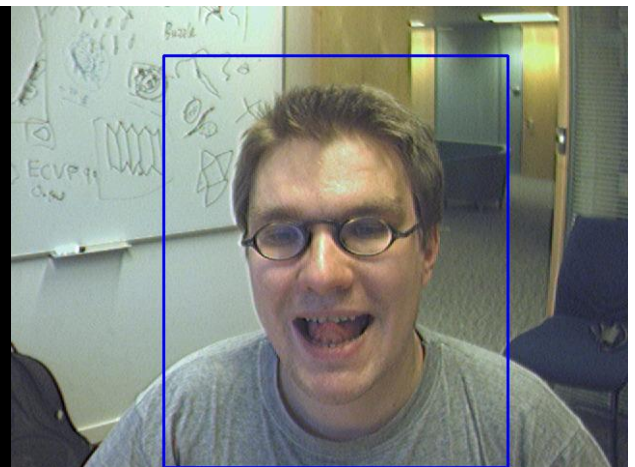
Loosest Fit



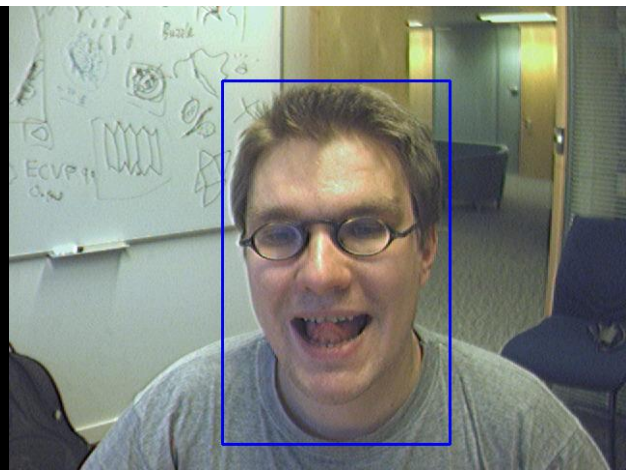
Loose Fit



Slightly Loose Fit



Tight Fit



Inference

A tight bounding box gives us the best results as it gives the background GMM model more background samples to model the background distribution. This is demonstrated above by using bounding boxes of varying fits. However, good results can be obtained using a loose bounding box but would need a lot of user editing to assist the algorithm in modelling the background properly.

Results

