DETECTING NUMBER OF CARS ON ROAD IN STILL IMAGE FOR AUTONOMOUS DRIVING

Step 1: Import important libraries which contain image processing packages.

Step 2: Read the image of interest. Convert it to a grayscale image

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

img= cv2.imread('car.jpeg')
img_gray= cv2.imread('car.jpeg',0)
plt.figure(figsize=(20,20))
plt.subplot(1,2,1)
plt.imshow(img_gray,cmap='gray', interpolation = 'bicubic')
plt.subplot(1,2,2)
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
```

```
<matplotlib.image.AxesImage at 0x7f574ce76690>
```

Step 3: Apply Otsu Thresholding to the image which automatically finds the optimum threshold value

```
ret2,th1 = cv2.threshold(img_gray,0,255,cv2.THRESH_BINARY+cv2.THRESH_OTSU)
plt.figure(figsize=(20,20))
plt.imshow(th1,'gray')
plt.title('otsu thresholding')
plt.xticks([])
plt.yticks([])
```

([], <a list of 0 Text major ticklabel objects>)

Step 4: Apply Median filter to improve the texture

```
median1 = cv2.medianBlur(th1,3)
for i in range(5):
 median1 = cv2.medianBlur(median1,3)
plt.figure(figsize=(20,20))
plt.imshow(median1,'gray')
plt.title('median filter')
plt.xticks([])
plt.yticks([])
```

```
([], <a list of 0 Text major ticklabel objects>)
```

Step 5: Perform Erosion and Dilation with disc shaped kernel to improve on texture

```
kernel1=np.array([[0,0,1,1,1,1,1,0,0],[0,1,1,1,1,1,1,1,0],[1,1,1,1,1,1,1,1,1],[1,1,1,1,
1,1,1,1,1],[1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1,1],[0,1,1,1,1,1,1,1,0
],[0,0,1,1,1,1,1,0,0]],dtype=np.uint8)
kernel2=np.array([[0,0,0,0,1,1,1,1,1,1,1,0,0,0,0],[0,0,0,1,1,1,1,1,1,1,1,1,0,0,0],[0,0,
1,1,1,1,1,1,1,1,1,1,1,0,0],[0,1,1,1,1,1,1,1,1,1,1,1,1,1,0],[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1
],[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1,1,1,1,
1,1,1,1],[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1],[1,1,1,1,1,1,1,1
,1,1,1,1,1,1,1],[0,1,1,1,1,1,1,1,1,1,1,1,1,1,0],[0,0,1,1,1,1,1,1,1,1,1,1,1,0,0],[0,0,0,1,
1,1,1,1,1,1,1,1,0,0,0],[0,0,0,0,1,1,1,1,1,1,1,0,0,0,0]],dtype=np.uint8)


img_erosion = cv2.erode(median1, kernel1, iterations=1)
img_dilation = cv2.dilate(img_erosion , kernel2, iterations=1)
plt.figure(figsize=(20,20))
plt.imshow(img_dilation,'gray')
plt.title('morphology')
plt.xticks([])
plt.yticks([])
```

```
([], <a list of 0 Text major ticklabel objects>)
```

Step 6: Perform Erosion and Dilation with Rectangular shaped kernel multiple times to separate the connecting region and invert the image.

```
median2 = cv2.medianBlur(img_dilation,3)
for i in range(10):
 median2 = cv2.medianBlur(median2,3)
img_new1=median2

kernel3= np.ones((15,15), np.uint8)
img= cv2.dilate(img_new1 , kernel3, iterations=3)
kernel4= np.ones((5, 5), np.uint8)
img1=cv2.erode(img , kernel4, iterations=3)
kernel5= np.ones((14, 14), np.uint8)
img2= cv2.dilate(img1 , kernel5, iterations=1)
img3=cv2.erode(img2 , kernel4, iterations=3)
img4=255-img3
plt.figure(figsize=(20,20))
plt.subplot(1,2,1)
plt.imshow(img3,'gray')
plt.title('mophology on image')
plt.xticks([])
plt.yticks([])
plt.subplot(1,2,2)
plt.imshow(img4,'gray')
plt.title('inverted version')
plt.xticks([])
plt.yticks([])
```

```
([], <a list of 0 Text major ticklabel objects>)
```

Step 7: Find the area of separated regions. Apply threshold on area. If less, then detected as car otherwise detected as background.

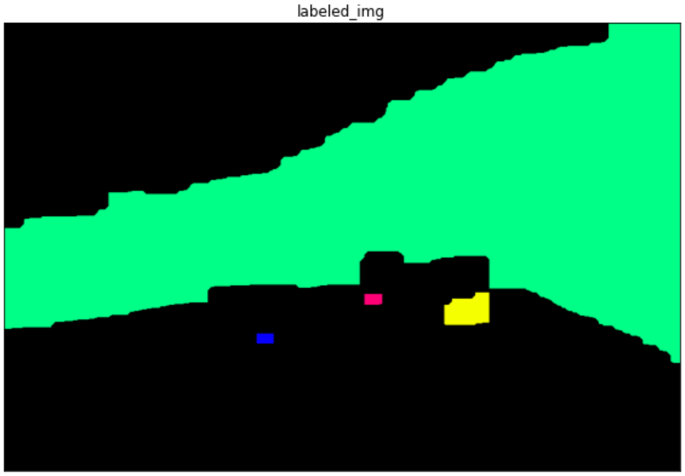
```
con=8
output= cv2.connectedComponentsWithStats(img4,con,cv2.CV_32S)
num_labels = output[0]
labels_im= output[1]
stats=output[2]
tot_area=0
count=0
area=list()
for i in range(0,num_labels):
 area.append(stats[i, cv2.CC_STAT_AREA])
print('area of the regions detected in decreasing order are',area)

for k in range(0,num_labels):
 tot_area=tot_area+area[k]
print('total pixels in image',tot_area)
for i in range(0,num_labels):
 if area[i]<= 0.02*tot_area:
    count=count+1

#num_labels, labels_im = cv2.connectedComponents(img4)
#print('total regions detected are',num_labels)
print('approximate cars in image are',count)
def imshow_components(labels):
 # Map component labels to hue val
 label_hue = np.uint8(179*labels/np.max(labels))
 blank_ch = 255*np.ones_like(label_hue)
 labeled_img = cv2.merge([label_hue, blank_ch, blank_ch])
 # cvt to BGR for display
 labeled_img = cv2.cvtColor(labeled_img, cv2.COLOR_HSV2BGR)
 # set bg label to black
 labeled_img[label_hue==0] = 0
 plt.figure(figsize=(10,10))
 plt.imshow(labeled_img,'gray')
 plt.title('labeled_img')
 plt.xticks([])
 plt.yticks([])
imshow_components(labels_im)
```

```
area of the regions detected in decreasing order are [308292, 193108, 2011, 319, 286]
total pixels in image 504016
approximate cars in image are 3
```

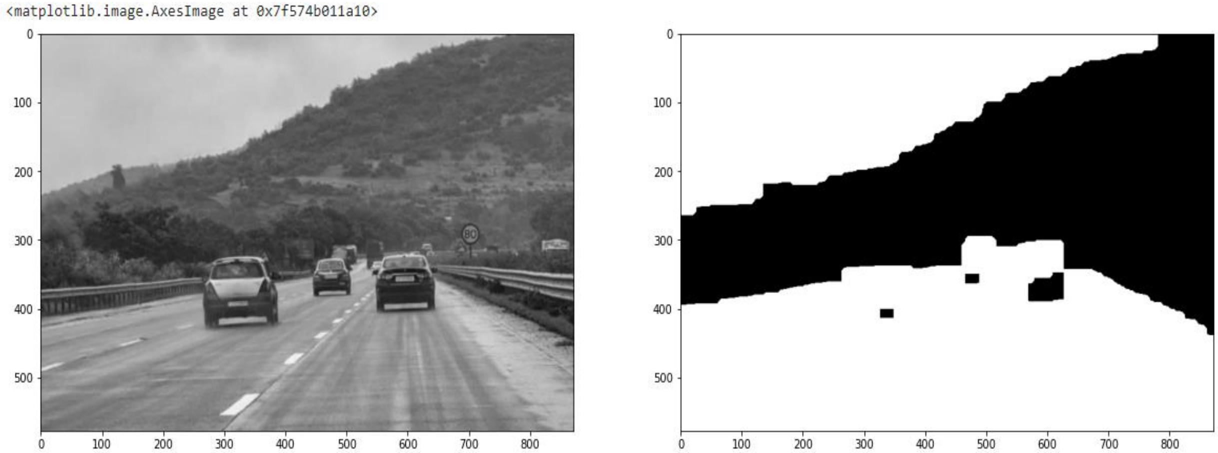
labeled_img



*****FINAL CONCLUSION*****

```
plt.figure(figsize=(20,20))
plt.subplot(1,2,1)
plt.imshow(img_gray,cmap='gray', interpolation = 'bicubic')
plt.subplot(1,2,2)
plt.imshow(img3,'gray')
```

<matplotlib.image.AxesImage at 0x7f574b011a10>



#Conlusion

Kernel in our project is image specific which states the fact that there is no ideal kernel which will work with all images. Hence further advancement can be done using Machine learning algorithm using convolutional neural network. The network itself tries to estimate the kernel after training with lots of training images.

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