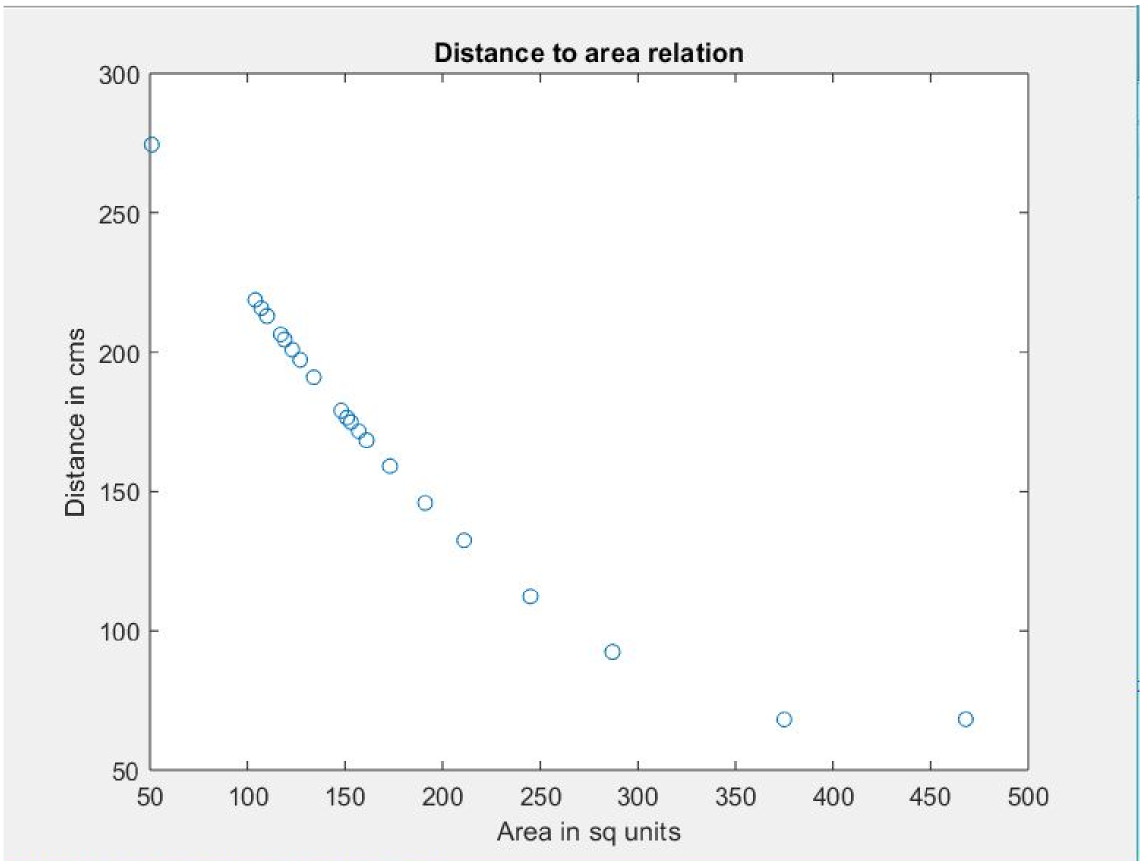
Project 1:Color Segmentation using GMM

David Linko & Rachith Prakash

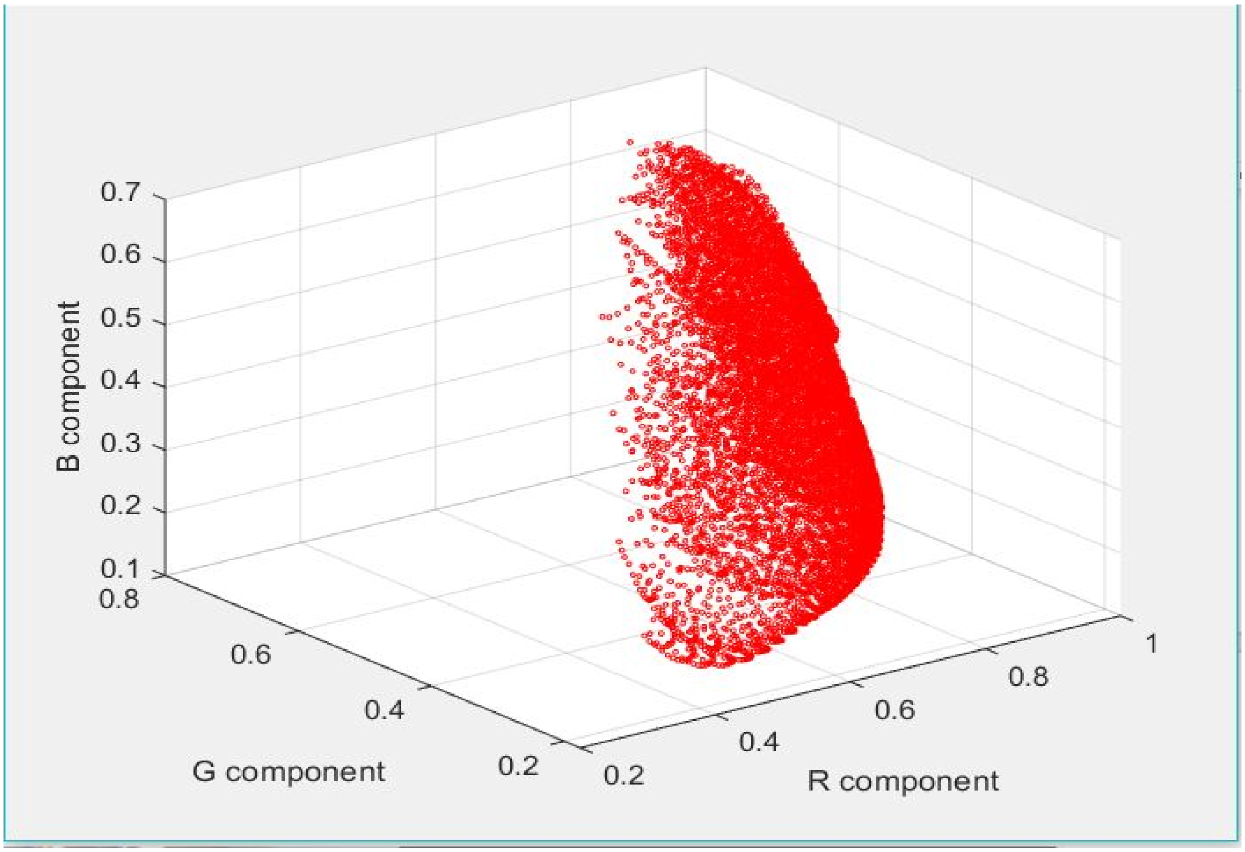
- Your choice of color space, initialization method and number of gaussians in the GMM.
  - We kept RGB color space for our modeling, as the R vs G vs B scatter plot of the training data points(orange pixels) were not too widespread and could be encompassed by couple of Gaussians.
  - In the GMM scenario, we need to initialize few parameters such as mean, co-variance, weights for each gaussian. These values were chosen to be random initially as they would converge later on.
  - The threshold for ball detection, i.e what should be the posterior probability of the data point for it to be considered orange was chosen random initially and later on changed manually to get desired orange ball.
  - Also, the ϵ (convergence criteria) threshold value used in GMM, was chosen randomly but with a low value as we want mean to converge until ϵ.
  - When choosing number of gaussian required, it is better to see how the RGB values of the training dataset is distributed i.e R vs G vs B scatter plot. A single Gaussian's ellipsoid will not be able to fit in all data points or even if it does, it might not be accurate as it would include points which are not from the dataset too. Hence, we choose multiple gaussians so that each Gaussian's ellipsoid will encompass parts of the region with more accuracy!. This will ensure that all/majority of data points are enclosed in either of the Gaussians. Thus, intuitively if the spread of the data points is sparse or cannot be bounded by a single Gaussian, we choose multiple Gaussians. The number of Gaussians depends on how the data is spread. If it is spread along a plane, a single gaussian would be sufficient, if, it is spread in many directions, we have to intuitively guess the number required. Based on the above reasoning, we chose 5 gaussians.
  - We also need to select the orange pixels of the ball from the training images. This was done by using the matlab function roipoly. These color values were then used to calculate the model.

- Explain why GMM is better than single gaussian.
  - Since the color orange's value can vary depending on the quality and lighting of the image, using a single gaussian can fail to capture the wide range color values that a single color can be perceived. The gaussian mixture model allows us to better bound the color. This is because it creates multiple gaussians each encompassing different ranges of pixel values of the same orange color.

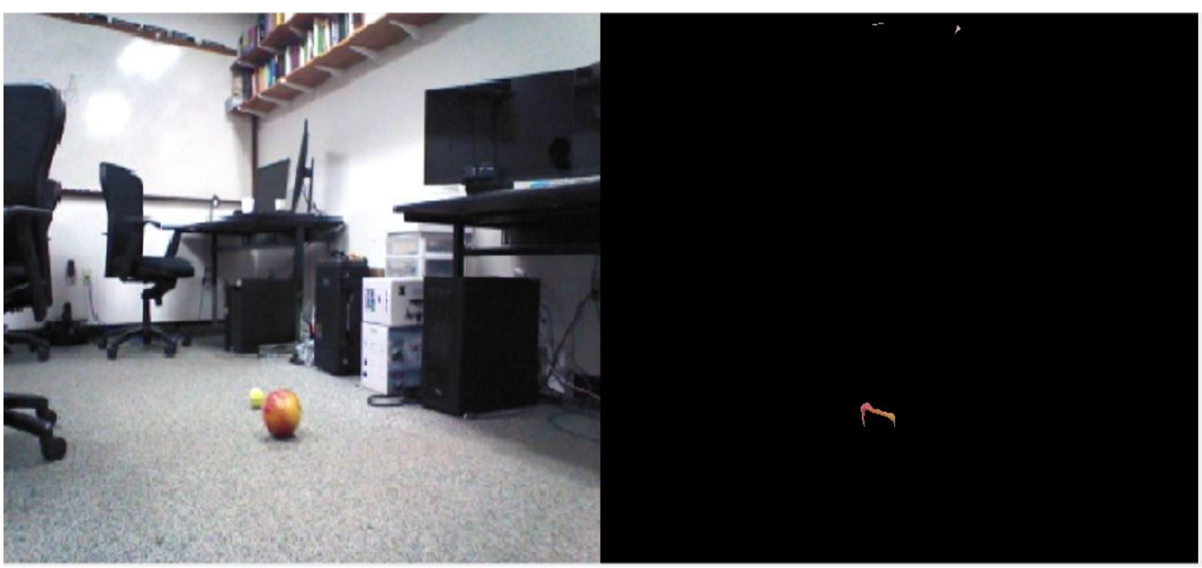
- Present your distance estimate and cluster segmentation results for each test image.
    - The relation between distance and area is obtained from the training data's info. Area is calculated using bemorph of the resultant image obtained. This area gives the number of pixels enclosed. Sp using polyfit, a 2nd order equation, the following graph is fitted with a curve.



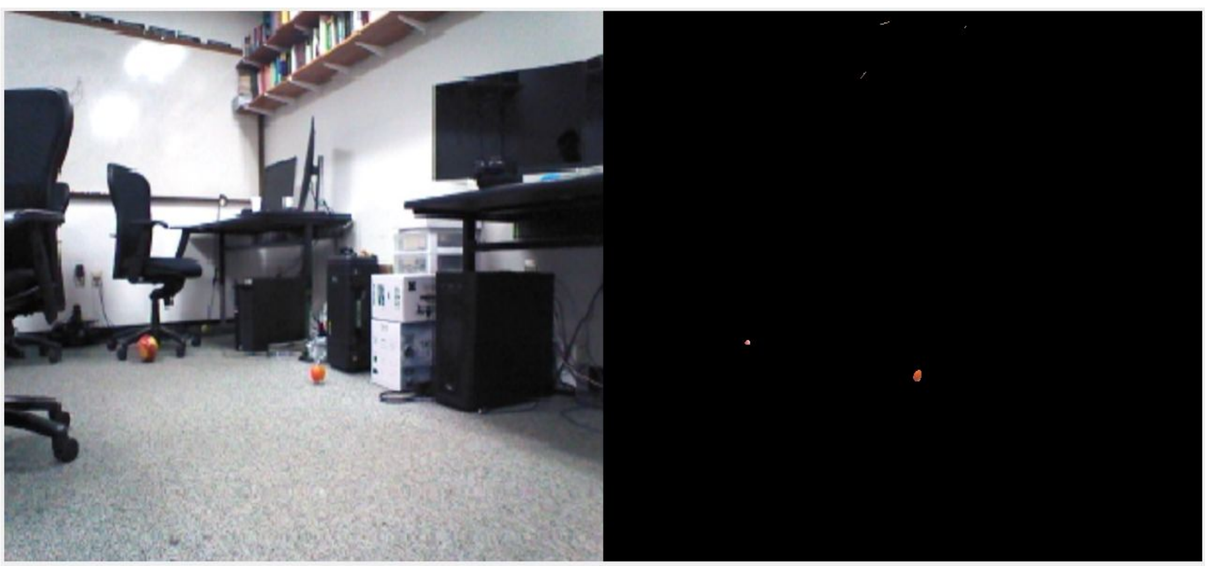
    - RGB plot of training data (orange dataset obtained from training images)

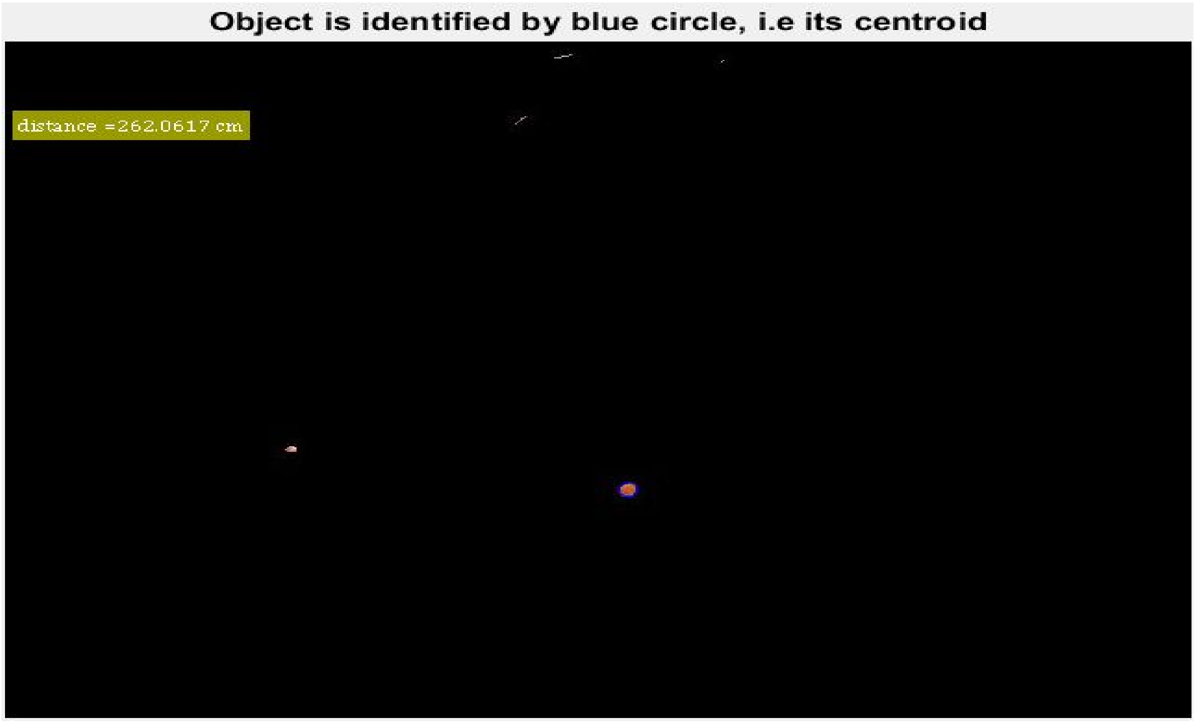


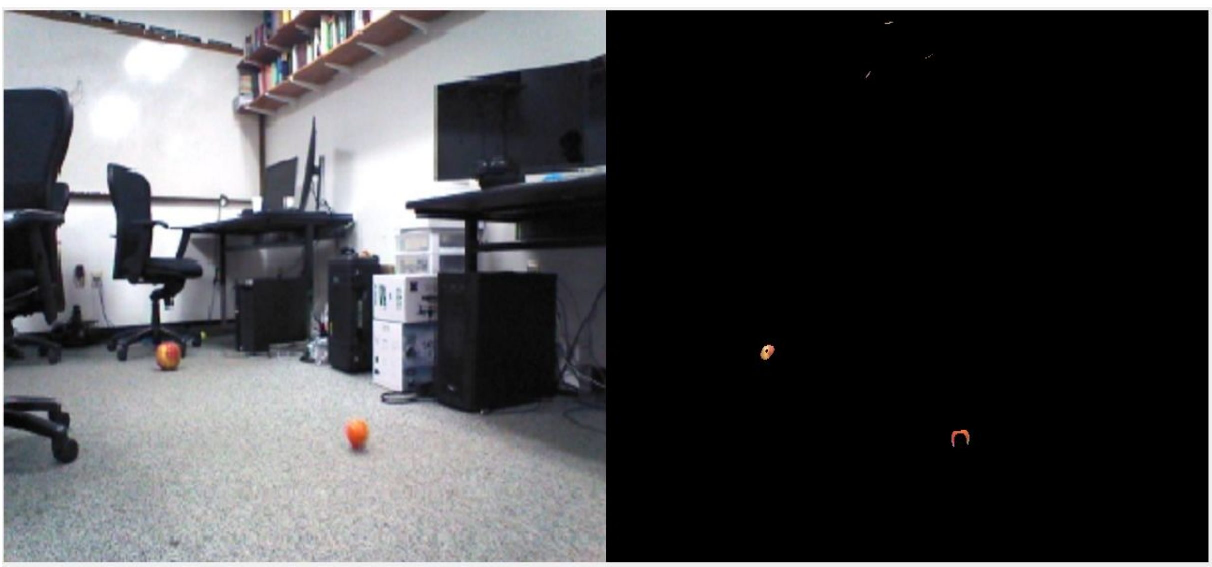
Single Gaussian Output and distances of the object(shown inside image),object identified by a blue circle:



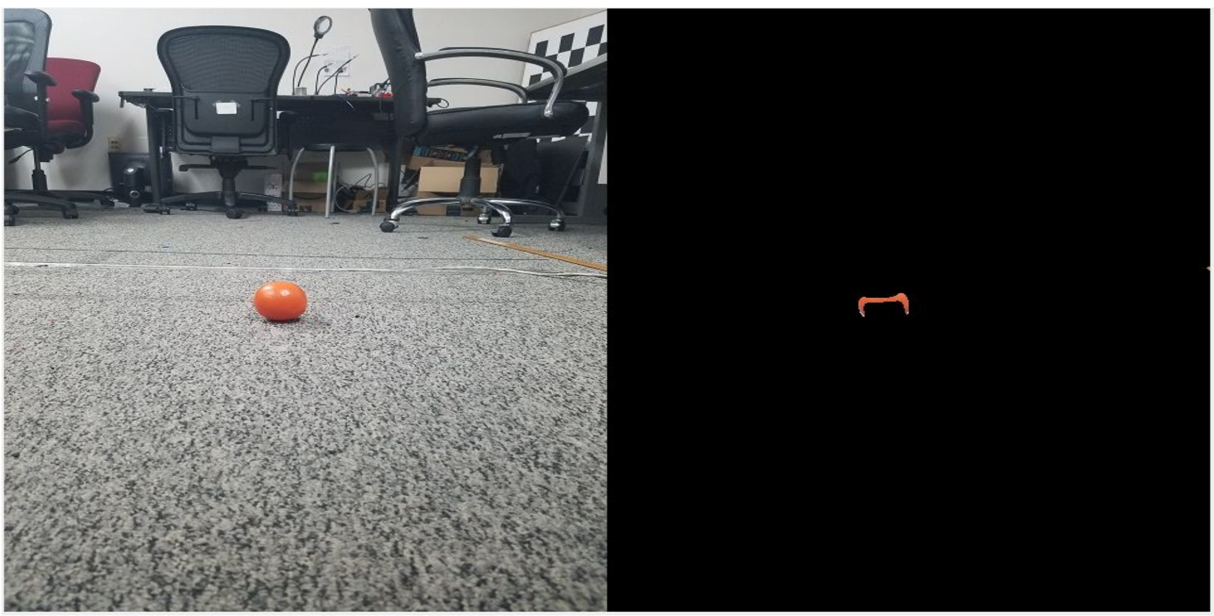

Object is identified by blue circle, i.e its centroid
distance =135.7243 cm

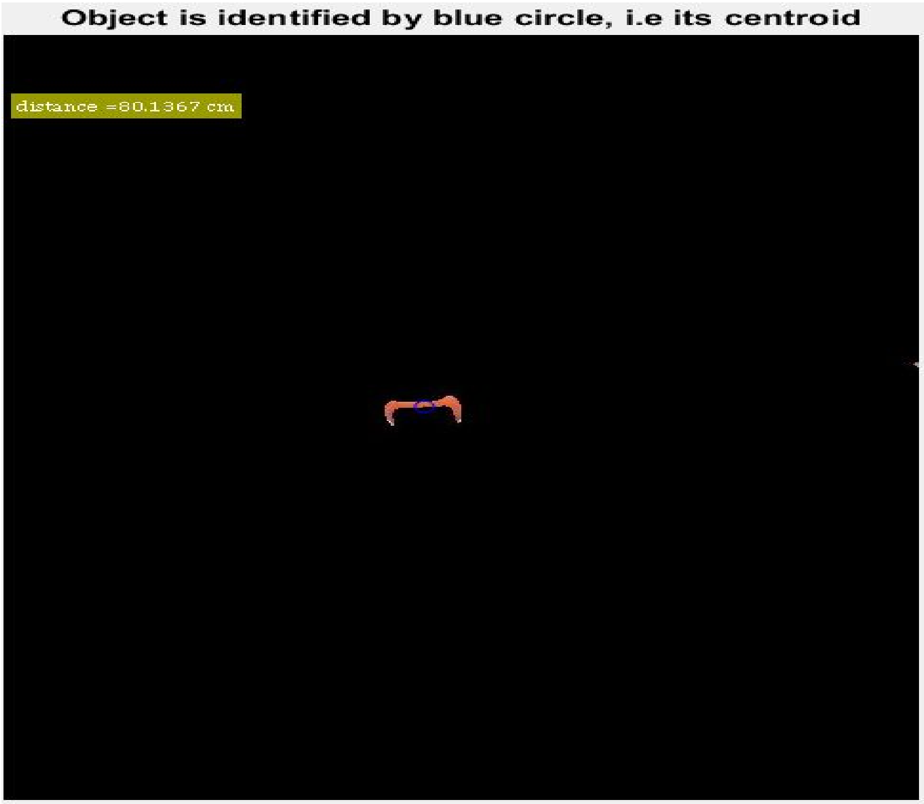


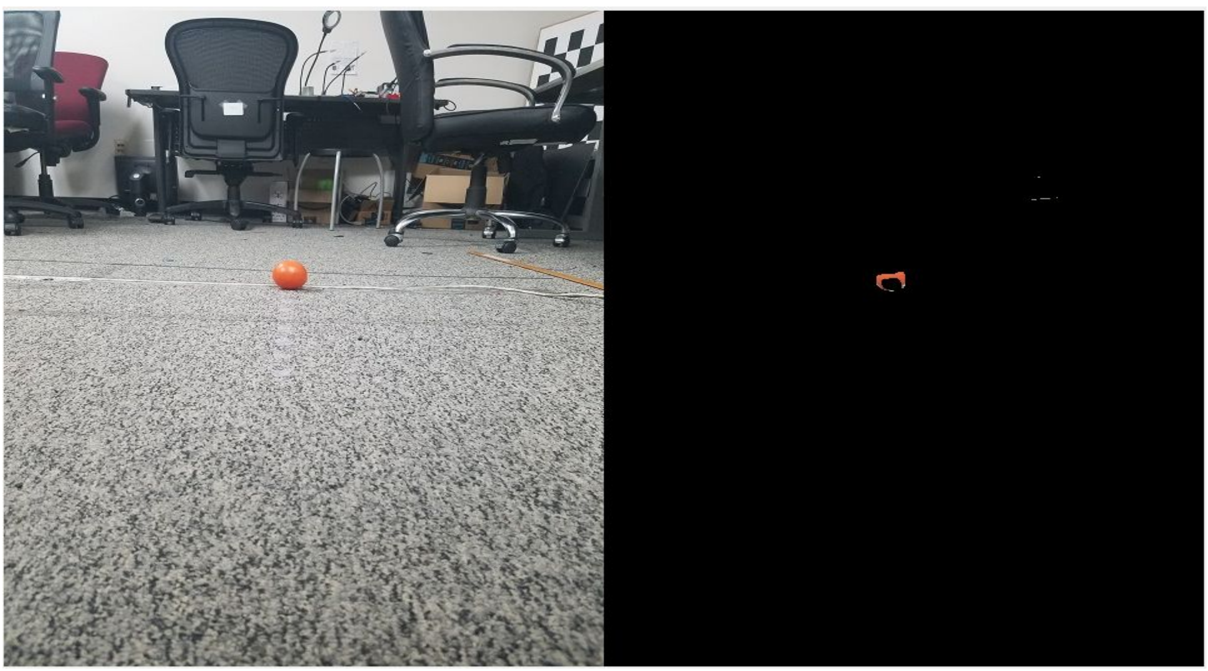

Object is identified by blue circle, i.e its centroid
distance =262.0617 cm



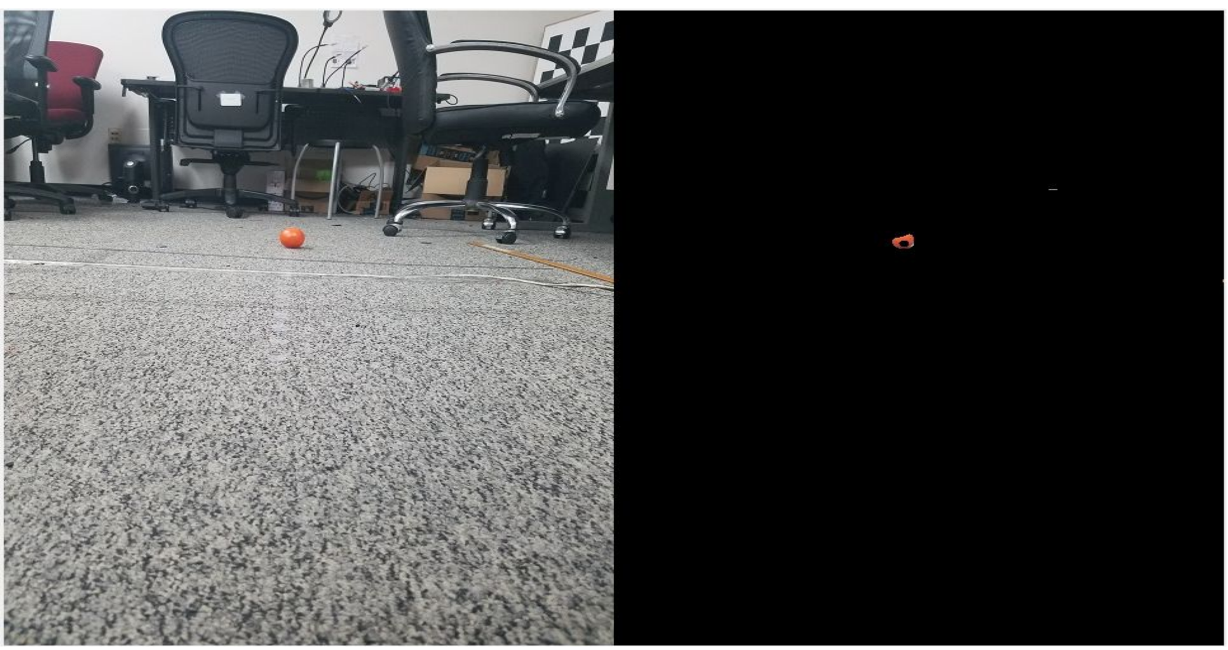

Object is identified by blue circle, i.e its centroid
distance =200.3785 cm

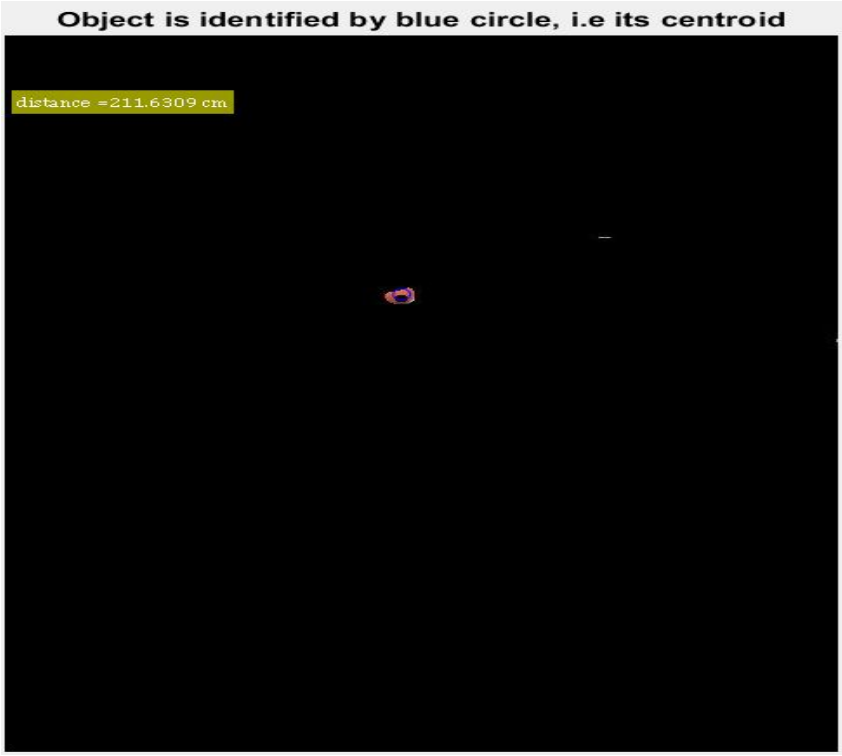


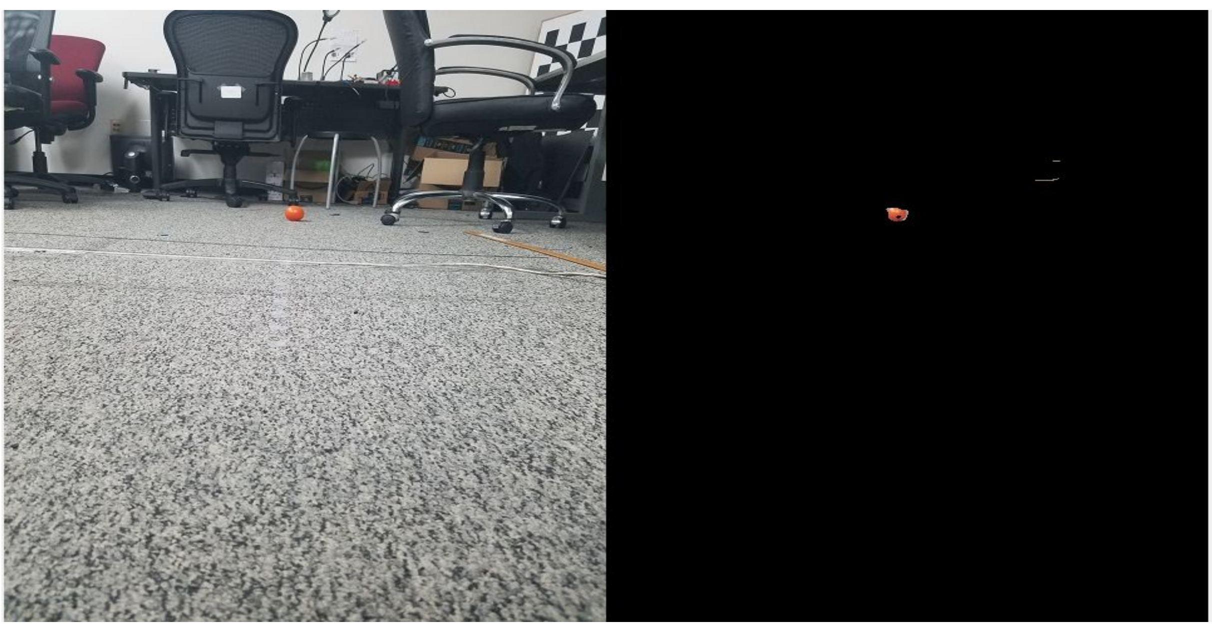

Object is identified by blue circle, i.e its centroid
distance =80.1367 cm

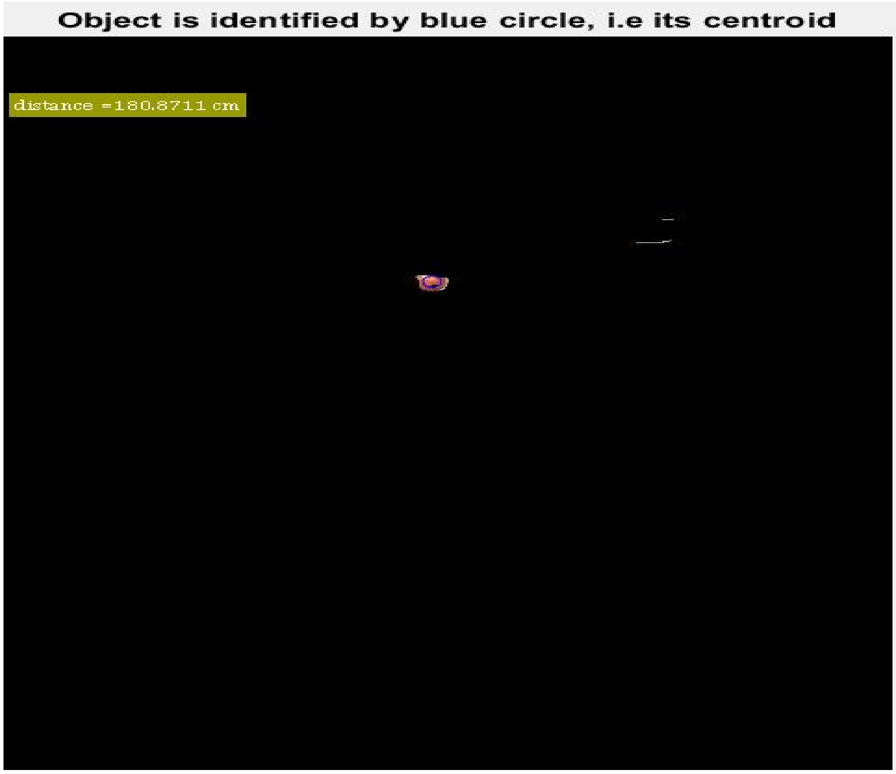


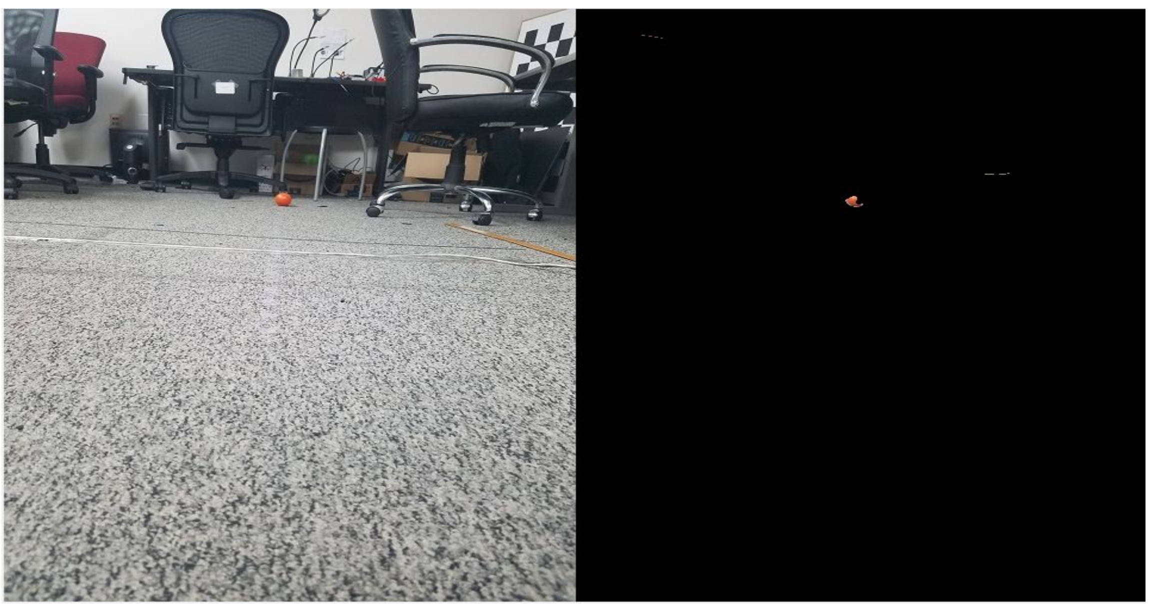

Object is identified by blue circle, i.e its centroid
distance =161.2463 cm




Object is identified by blue circle, i.e its centroid
distance =211.6309 cm

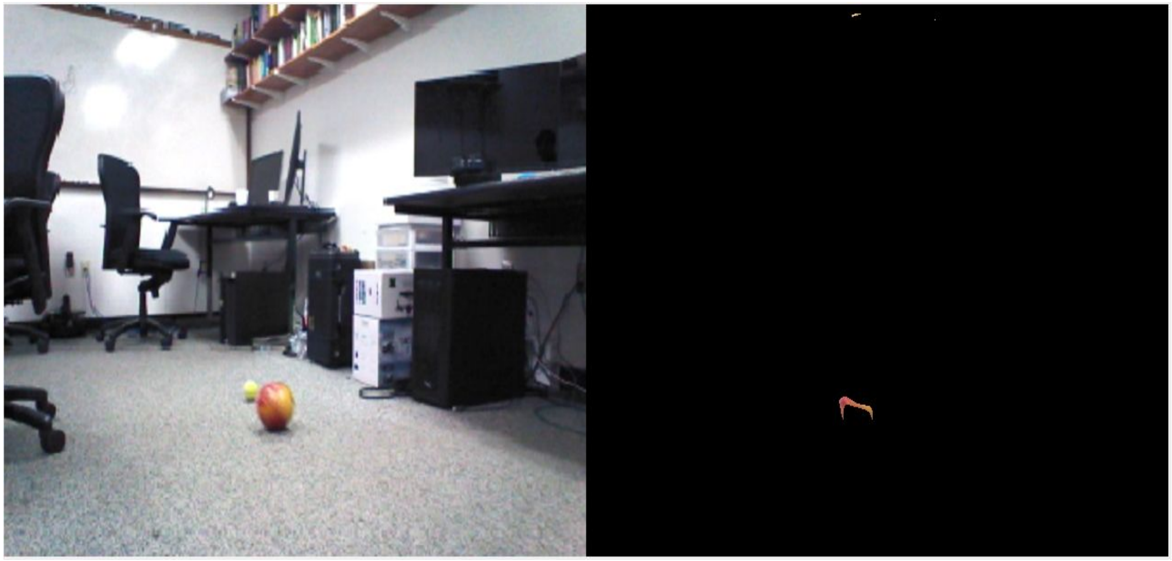


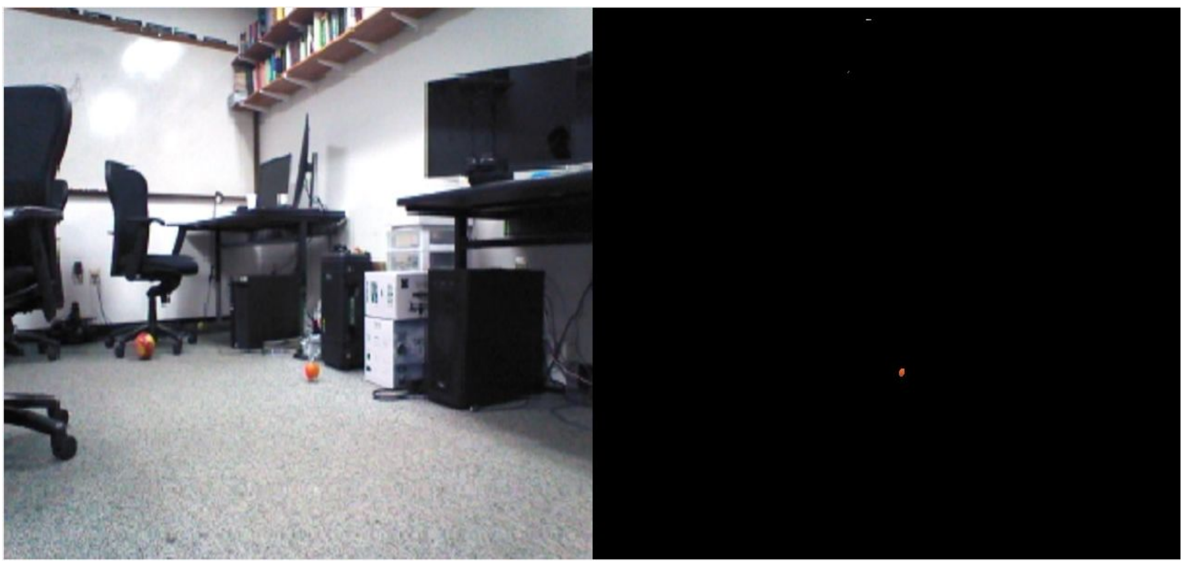

Object is identified by blue circle, i.e its centroid
distance =180.8711 cm

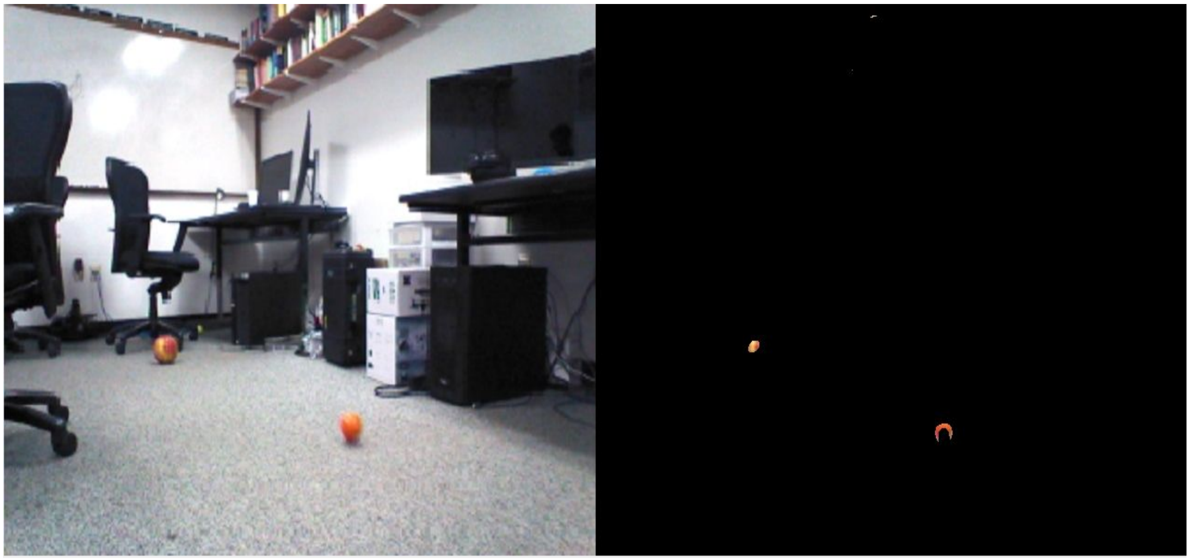


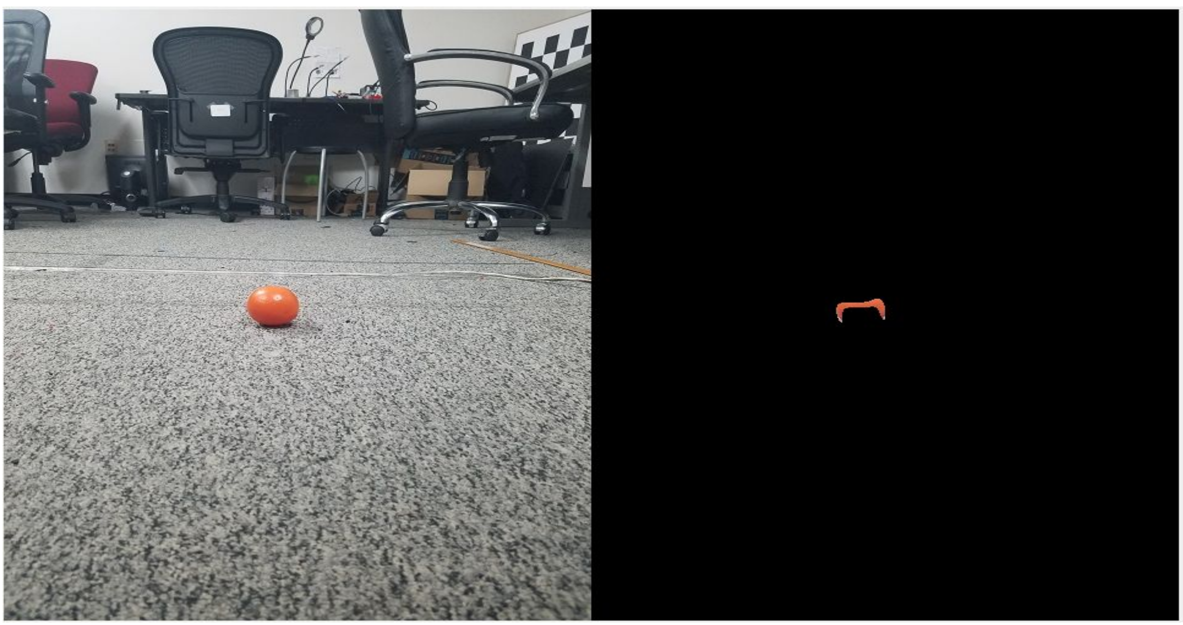
Multiple Gaussian Output:

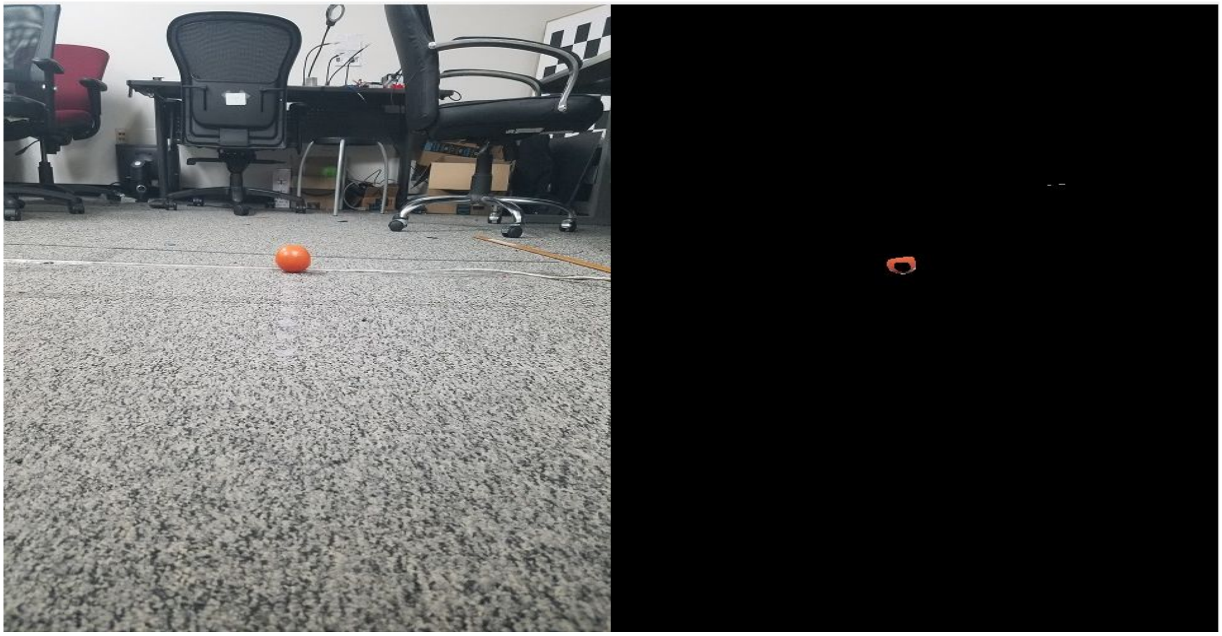
Used K = 5, where K = number of Gaussians.

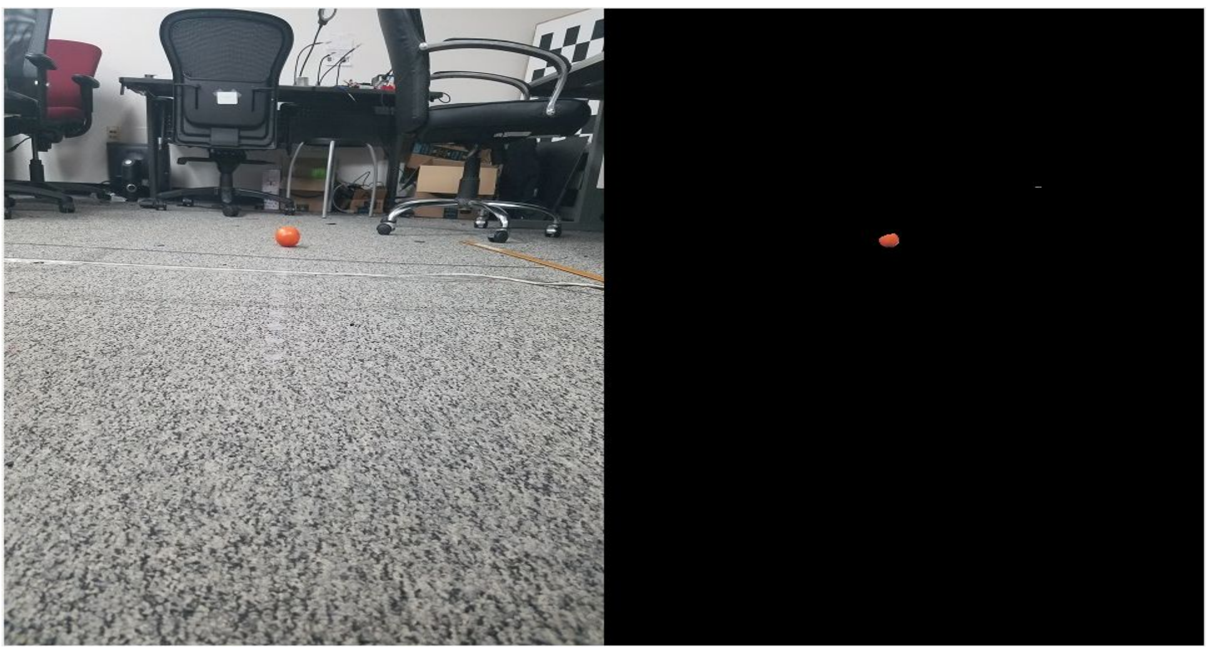


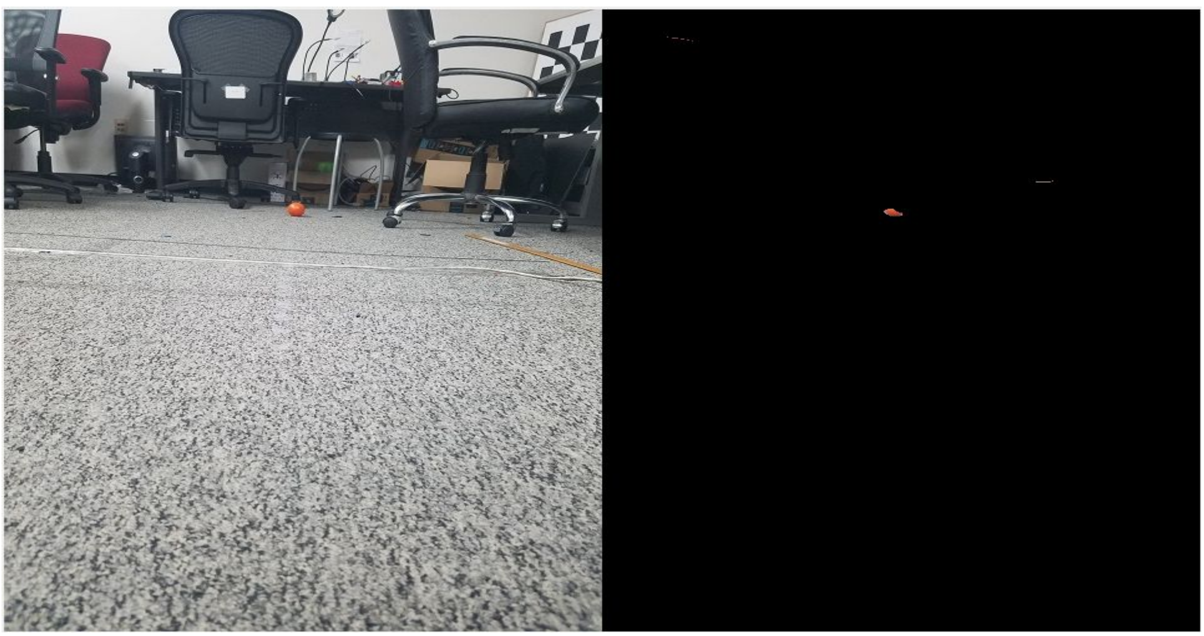












- Explain strengths and limitations of your algorithm. Also, explain why the algorithm failed on some test images.

  - Strength would be that if given a proper training set to train our algorithm, by this I mean, training set should also include images from different lighting conditions, algorithm would perform better.
  - Lighting and image quality greatly affects the ability of our algorithm to perform effectively. If a test image has very different lighting condition than what we used to train our model, our model would not recognize the ball as orange. This is because the value of the color pixel as perceived by the camera would not be that of an orange.
  - The algorithm failed on Image1 because, the apple in the image is blurred and the lightning is different a bit and our algorithm took it as an orange (only some portion as seen in the output). In Image 2, there were 2 objects detected because of the the angle at which it was captured was different and partially because of blurring.
  - Also, our algorithm did not accurately get the entire orange ball even when it was near because of smoothing (Gaussian filter that we applied initially) if what we think. The magnitude of sigma chosen for training the data determines the value of orange dataset. Hence, we had to choose the optimal value.