University Of Maryland

College Park

Project Report

673-Perception for Autonomous Robots

Project 3

Aditya Goswami
116951968

Mahmoud Dahmani
116777896

Sukoon Sarin
116955522

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Contents

List of Figures

1 Introduction

The project is to implement Colour segmentation using Gaussian mixture model (GMM) and Expectation Minimization (EM) algorithm.

- 'Buoys' are distinctly colored and shaped floating devices used as underwater markings for navigation and can be segmented using color segmentation.
- However owing to the environmental noise and change in light intensities it is challenging and difficult to segment the buoys using color threshold techniques.
- Hence, we aim to get a tight contour over the segmented buoys using Gaussian Models to learn the color distribution and using the model to segment and detect the buoys.
- Further below is the detailed report of our steps for each problem.

2 Data Preparation

1. First we determine the total number of frames in the video clip and divide the frames to 7:3 ratio for training and testing frames. In our case we had total of 200 frames, thus we chose to take 140 frames for testing purpose and extracted 28 frames at a certain intervals from all over the video.

2. After extracting the test frames we crop the different coloured buoys and save it in different folders. The cropping is performed tighter to the outline of the buoy for minimal noise inclusion.

3. After performing all these operations it is observed that we do not need so many data for training purpose, thus we removed some of the data and started visualizing the average histogram for each BGR channel for each buoy.

4. After deciding which channel gives the best output for each coloured buoy we start training the parameters i.e., mean and standard deviation for colour segmentation.

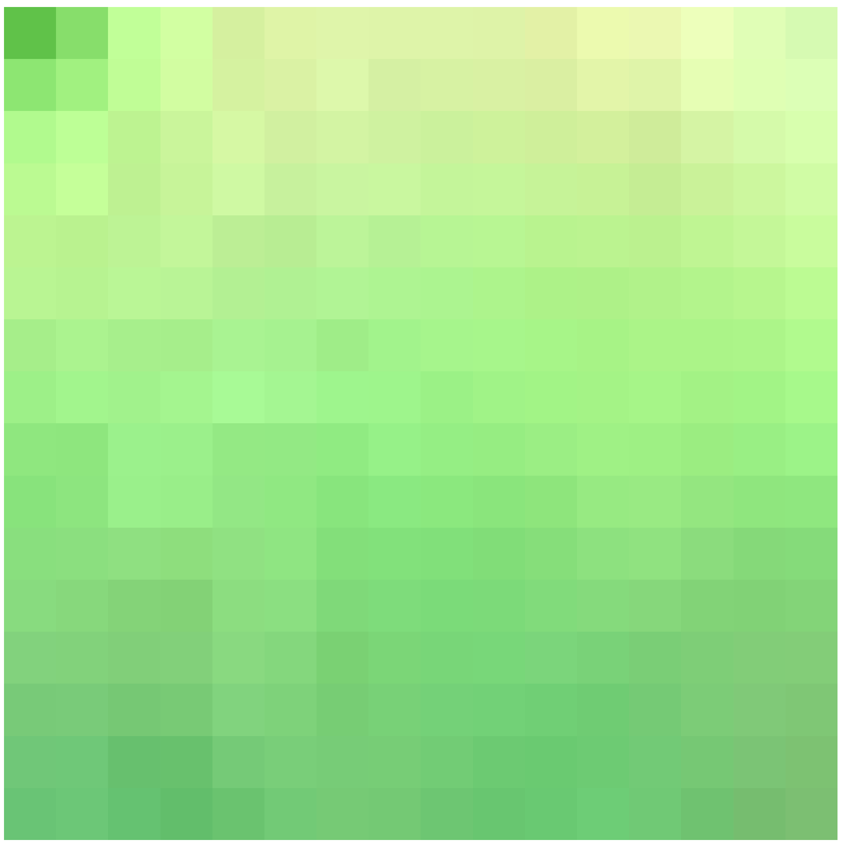

Figure 1: Green Image Cropped

Figure 2: Yellow Image Cropped

3 Average Histogram

1. Average histogram is drawn by averaging all the histograms for each frame i.e. first the histogram is drawn for each frame and then all data from all the histograms are averaged together to make an average histogram for the whole video.

2. Average histogram is shown for each of the channels i.e. BGR for each buoy.

3. The thing to notice in the average histograms was the number of pixels along the peak in each channel.

4. For orange buoy the number of pixels along the peak of the red channel were about 100, around 80 more than the blue and green channel, hence only red channel is used for the orange buoy for further processing.

5. Similarly for green buoy the peak along green channel was higher than the peak about blue and red channel, hence only green channel for the green buoy is used for further processing.

6. For the yellow buoy, the peak about the red and green channels were comparable, hence the average of the red and green channel is used for the further processing.

7. This gives the intuition of which channels should be used in training and also gives an idea about the pixel intensities distribution.

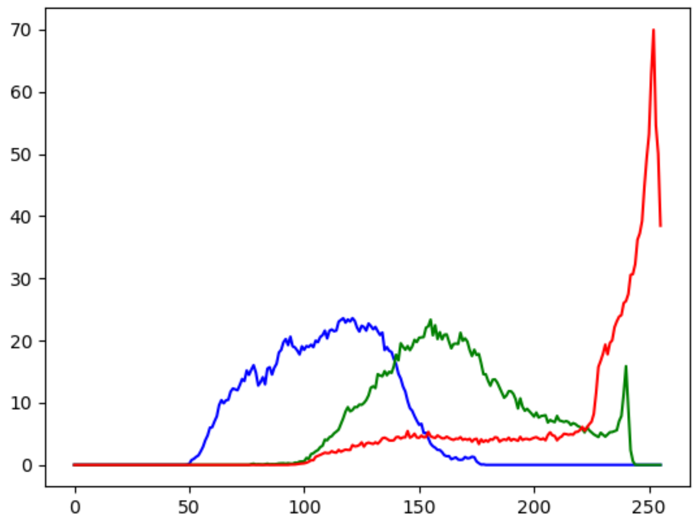

Figure 3: Orange Buoy Average Histogram

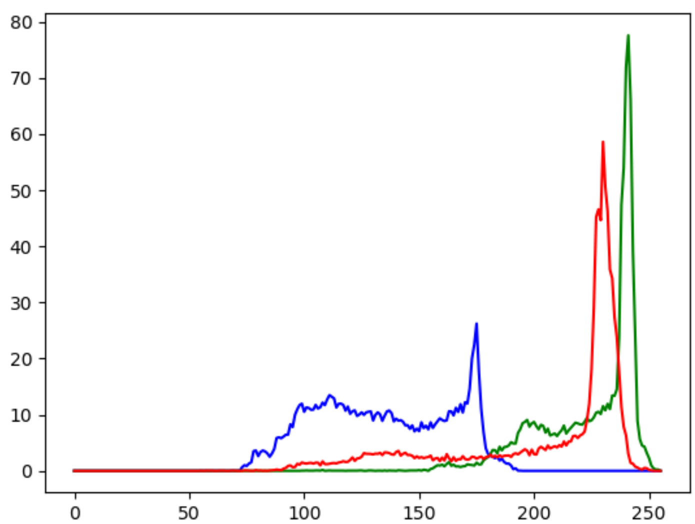

Figure 4: Yellow Buoy Average Histogram

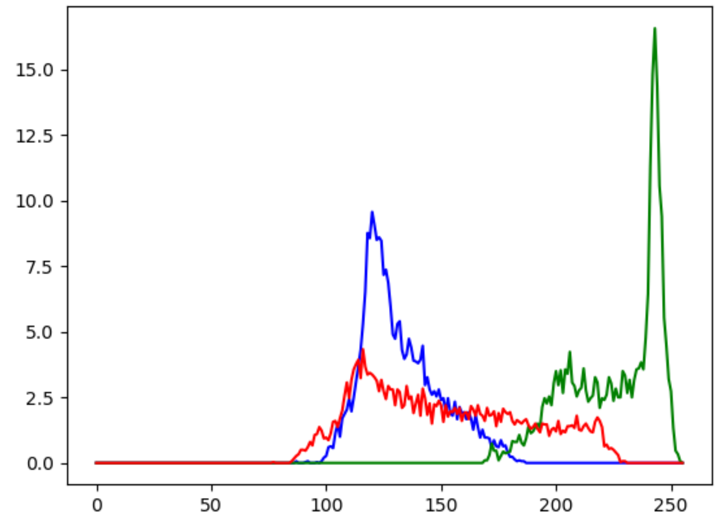

Figure 5: Green Buoy Average Histogram

4 1D Gaussian

1. After calculating the average histogram we now aim to fit a 1D Gaussian over it.

2. We first load the training data set and look at the channel of which the histogram is of maximum intensity for that buoy and extract that channel for the training.

3. If it is a single channel then it is passed in the variable $flat\_array$ as a list. If it is more than one channel then we add those channels and divide by the number of channels added together.

4. That is for the orange buoy we see that the average histogram has the maximum intensity in red channel. For yellow it is both red and green and for green it is only in green channel.

5. After loading that particular channel we calculate the mean and standard deviation of all the images of train set for that buoy.

6. This mean and standard deviation is then used to generate the Gaussian using the equation :

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{1}$$

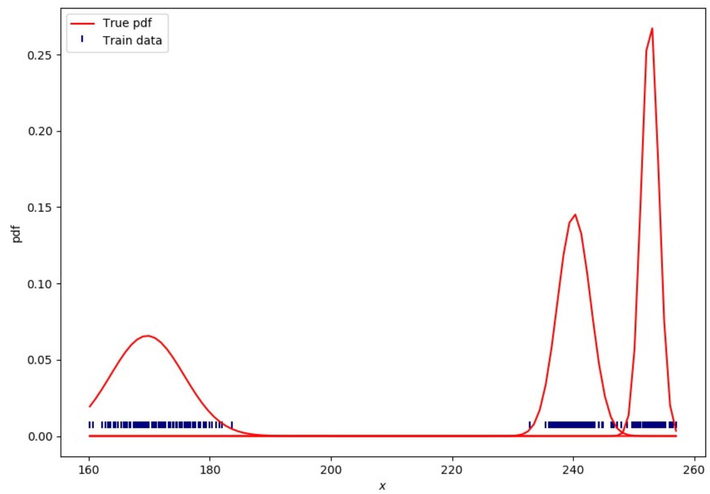

Figure 6: Red Gaussian

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2}$$

7. The images of the Gaussian generated has been depicted below.

8. Once the Gaussian are generated we put a threshold on the probability and thus detecting the buoy for that particular color.

9. The images of the same are depicted below but we see that the images are not proper and thus we use the further approach.

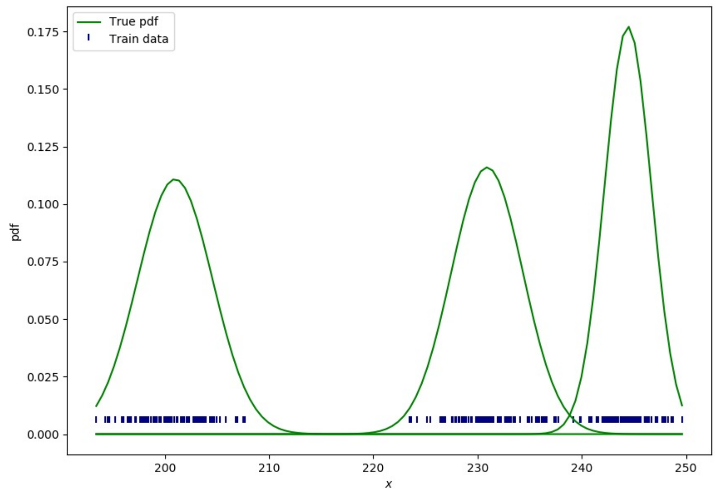

Figure 7: Green Gaussian

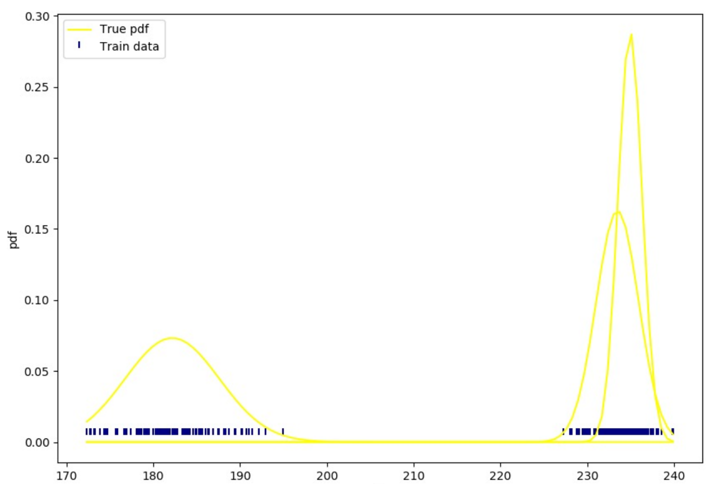

Figure 8: Yellow Gaussian

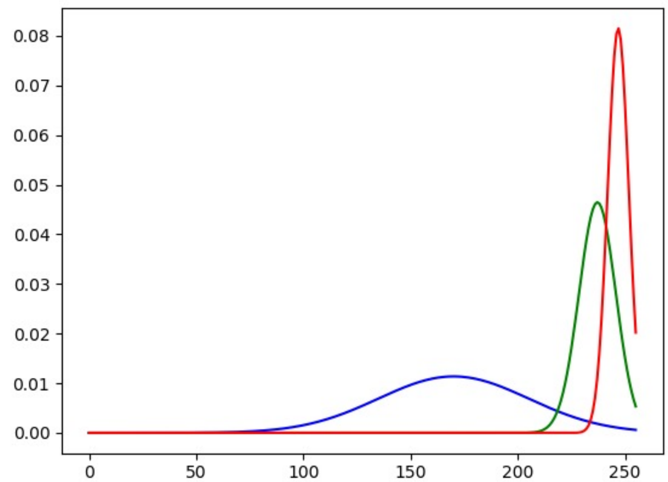

Figure 9: Green Gaussian Mixture

5 Gaussian Mixture Model and Expectation Maximization

1. A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. It can be thought that the GMM is a generalized k-means cluster to incorporate information about the variance structure of the data and the centers of the Gaussian formed.

2. The main difficulty in GMM algorithm is that the data is unlabeled, so one cannot determine which point came from which latent component. Expectation-maximization algorithm solves this problem through iterative process. At first we select random components (i.e., randomly selected center points and a common standard deviations) and compute for each point the probability of being generated by each component of the model. Then we tweak the parameters i.e., mean and standard deviations of each Gaussian formed for each considered channels. Repeating this process guarantees to always converge to a local optimum values.

   The Gaussian/probability from the mean and standard deviation is found out using the following equation:

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2 / 2\sigma^2}$$

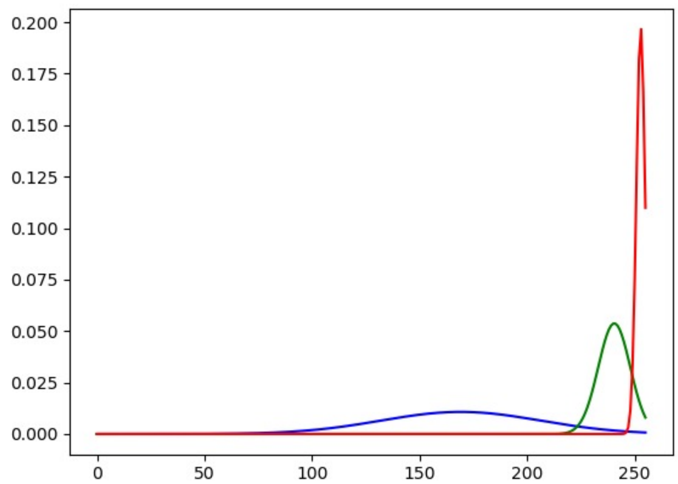

Figure 10: Red Gaussian Mixture

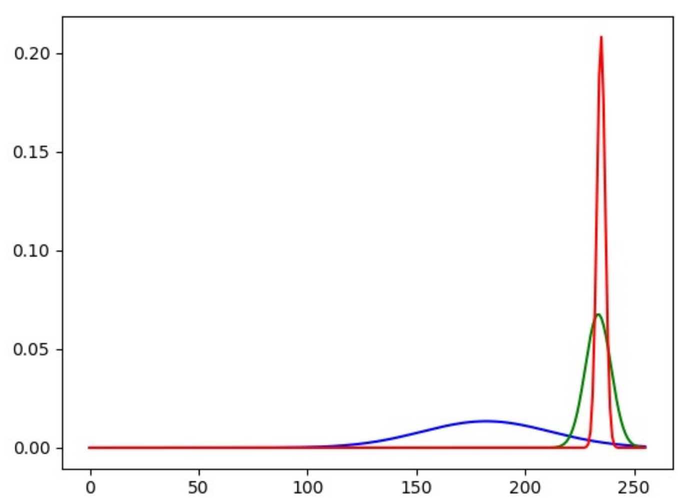

Figure 11: Yellow Gaussian Mixture

6 Using EM to extract GMM Parameters

1. Generate 3 random samples for three 1-D Gaussian with different means and standard deviation.

2. The equations used are -

$$\Pr[A_i|E] = \frac{\Pr[E|A_i]\Pr[A_i]}{\sum_{i=1}^{n}\Pr[E|A_i]\Pr[A_i]}$$

$$L(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \prod_{i=1}^{n} \frac{1}{|\boldsymbol{\Sigma}|^{\frac{1}{2}}(2\pi)^{\frac{p}{2}}} \exp\left\{-\frac{1}{2}(\mathbf{x}_i - \boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{x}_i - \boldsymbol{\mu})\right\}$$

$$Mean = \frac{\sum(Bayesian\ Probability)(pixel\ intensity))}{\sum(Baysian\ Probability)}$$

$$StandardDeviation = \sqrt{\frac{\sum(Bayesian\ Probability)(pixel\ intensity))}{\sum(Baysian\ Probability)}}$$

3. These three 1-D Gaussian formed are applied to all the test images stored in the folder.

4. After running it through all the images we get a new mean and standard deviation.

5. These new values are used and again applied to all the images, and this step is iterated for 50 times.

6. After executing the process for 50 times the mean and the standard deviation converges and does not change, these values are the trained values and are used for further analysis. 50 has been chosen as the iteration number because the log-likelihood function converges in this time.

7. This gives us the final values of mean and variations for three gaussians.

7 Learning Color Model and Buoy Detection using GMM

1. This part of the project basically involves to identify how many Gaussian and dimension of Gaussian to be used to detect and segment the colored buoys
2. After several iterations we have identified that one dimensional Gaussian will give better results and since we can fit it to the histogram of that particular colour will give us a better understanding of the segmentation in terms of noise and actual buoy.
3. For the orange buoy, we have taken the histogram and plotted the three 1-D Gaussian and we notice that it completely matches the average color histogram of red channel.
4. Similarly we compute the same process for the rest of the buoy to and we keep of generating the Gaussian until it clearly fits the histogram.
5. The images of the histogram along with the Gaussian used to fit has been depicted below.
6. Once the Gaussian have been generated to fit the histogram the Y axis represent the probabilities.
7. We segment every pixels according to the (probabilities) thus stating a threshold on the probability of that pixel being in that Gaussian.
8. We create a binary image after applying threshold according to the probabilities and find the contour of that buoy.
9. After this point we trace back the contour on the original frame of the video, and it is depicted in the images below.

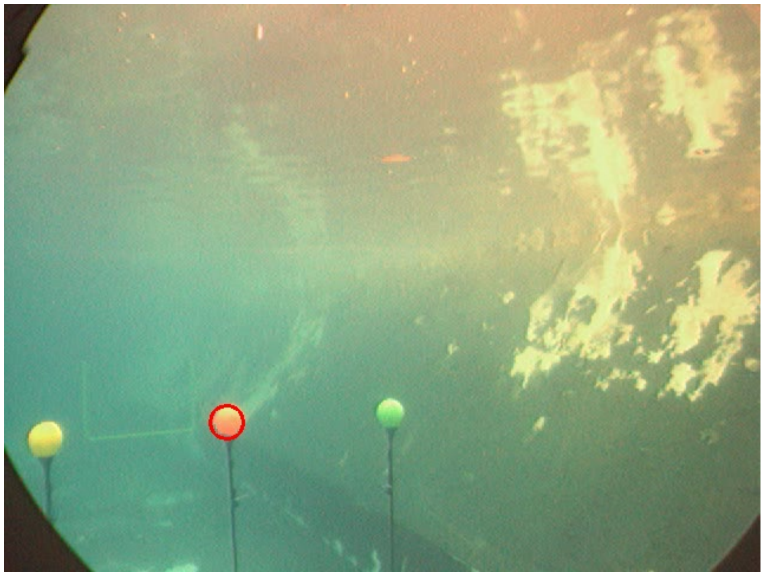

Figure 12: Red Buoy Detection Only

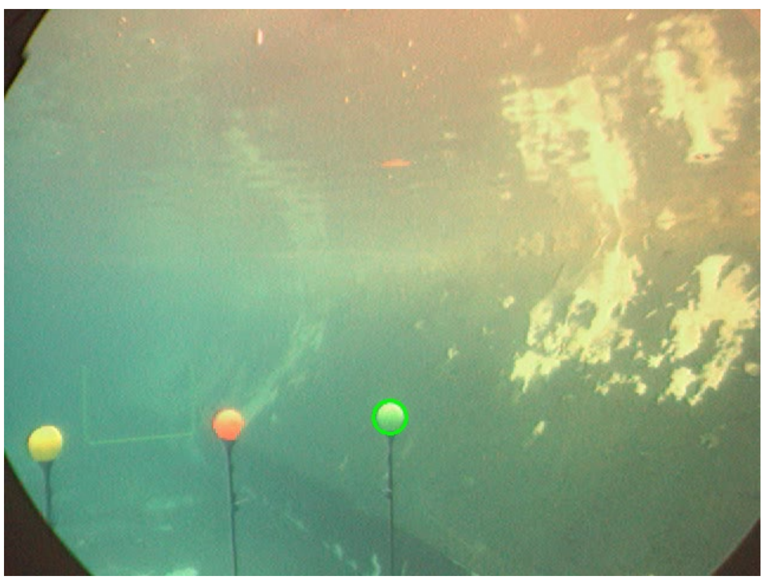

Figure 13: Green Buoy Detection Only

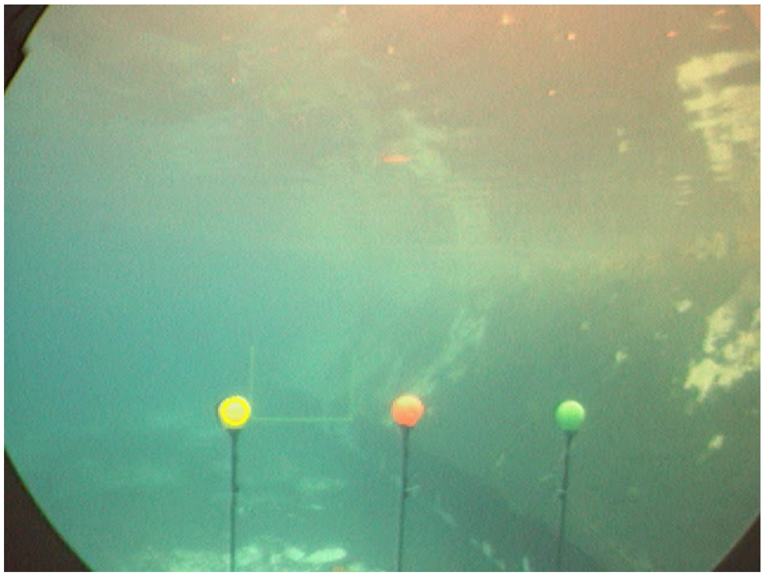

Figure 14: Yellow Buoy Detection Only

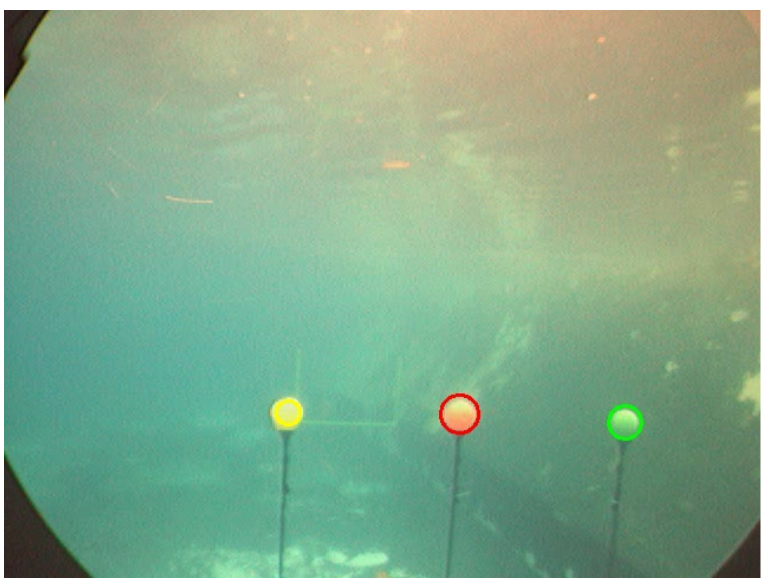

Figure 15: All buoys detection

8 Problems faced and their analysis

1. We only used BGR color space for the implementation of this project.

2. Only using three 1-D Gaussian on the red channel of the orange buoy gave excellent results.

3. Only using three 1-D Gaussian on the green channel of the green buoy gave good results with some background error. Background error can be removed by using morphological operations such as dilation and erosion. Background error can also be removed by using contouring operations. But the downside of only using contouring operation is that it does not work on all the frames. Using contouring operations after morphological operations gave us good results.

4. Yellow buoy was the most difficult to identify as the yellow color background error due to sunlight is present in the initial frames of the video.

5. Only using three 1-D Gaussian on on one of the channels of the yellow buoy gave no results, hence we used three 1-D Gaussian on the average of the green and red channel. Using contouring operations after morphological operations (erosion and closing) gave us good results, with only some background error in the initial frames.

6. We feel that different color space such as HSV and BGRY can be used for this project. BGRY has its own yellow channel, hence will make it easier to detect yellow color buoy in the input video.

7. We had a great help from all these resources:

   - Lecture notes and pdf.[1]
   - Computer Vision, A Modern Approach [2]
   - Expectation maximization and gaussian mixture models.[3]

References

[1] Prof. Charifa. *ENPM-673*.

- Lecture notes and pdf.

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[2] Forsyth and Ponce. *Computer Vision, A Modern Approach*.

- Pdf - Computer Vision, A Modern Approach.

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[3] Pythoncourse. *EM and Gaussian Mixture Models*.

- EM and Gaussian Mixture Models.

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