

Name: Iyer Krithika Ganesh Sundaram

UNID: u1135255

Email ID: u1135255@utah.edu

Project 2

A. Image colorization

1. A histogram equalizing transformation routine

As described in the requirement, a program for calculating the histogram equalisation transform has been implemented. The input to the function:

- Input gray image.

For the given binary image, a simple histogram is calculated first. Then the probability distribution of the pixels is calculated by dividing the frequency of occurrence (from histogram) of each pixel with the total number of pixels in the image. Next the cumulative distribution function of the pixels is calculated. This cumulative distribution function is the histogram transformation which when applied to the original image will give us the equalised image.

Example 1:

For the given input image, the Normalised histogram is array is returned.

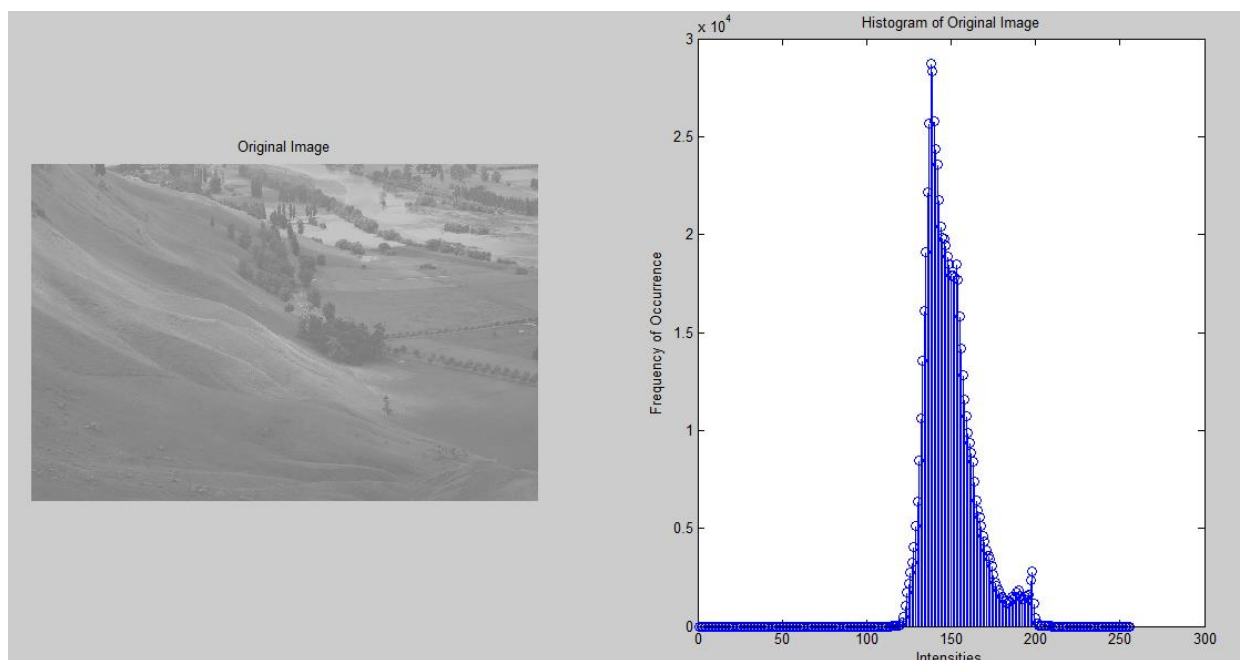


Figure 1

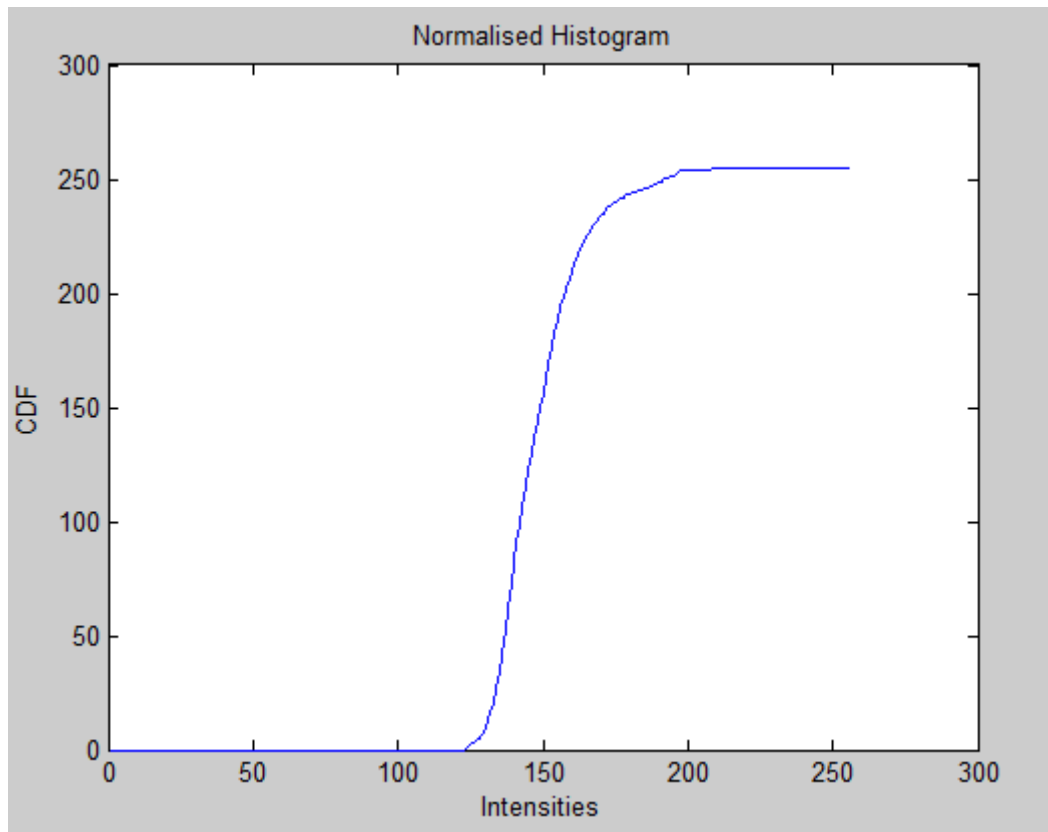


Figure 2

Example 2:

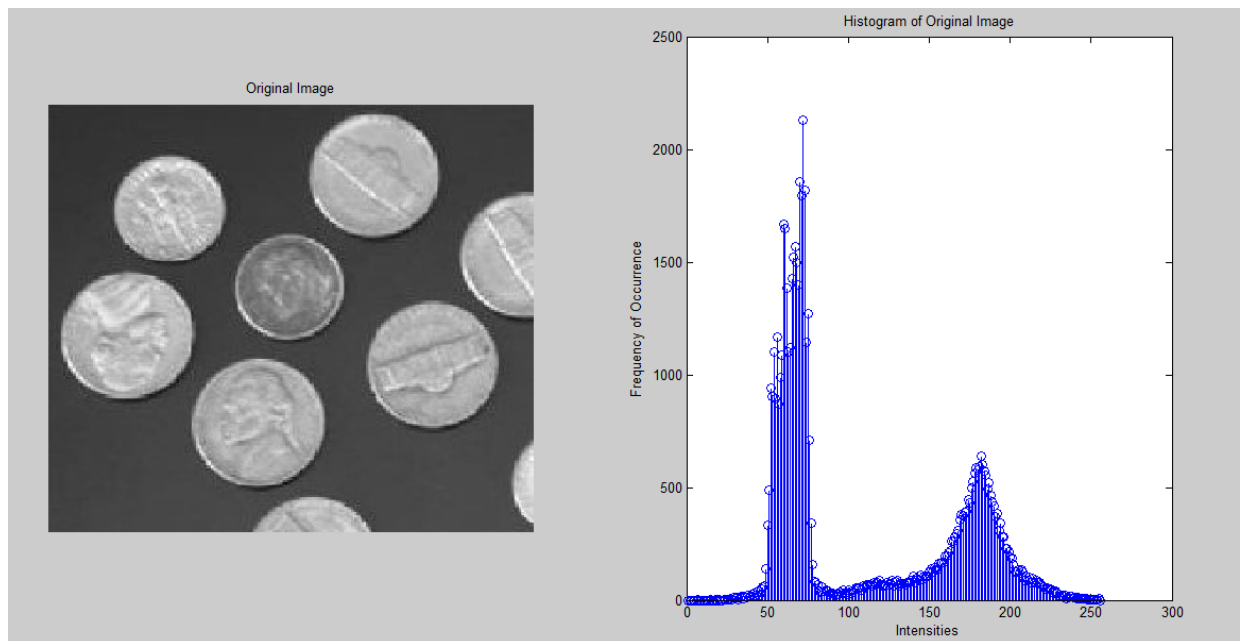


Figure 1

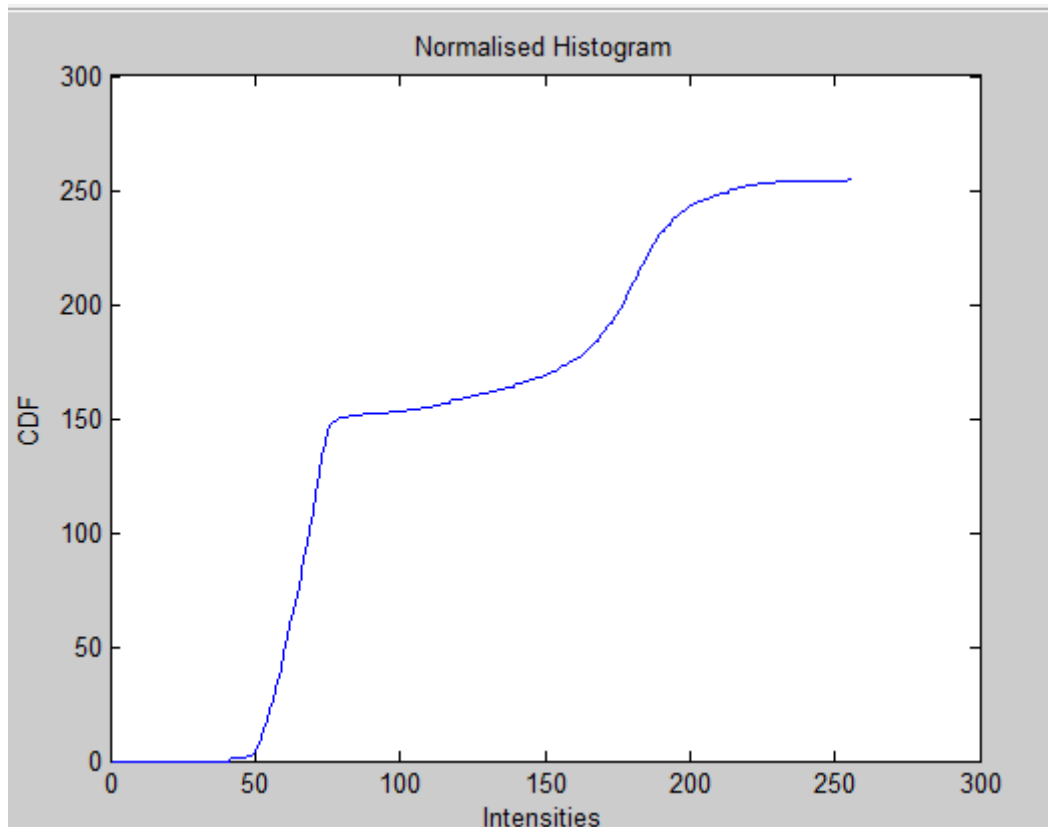


Figure 2

CODE: *myhisteq.m*

2. An intensity transformation routine

As described in the requirements, a program to perform intensity transformation has been implemented. For the transformation, the value of the transformation array at the index equal to the input image intensity is taken and applied to the output image.

The input to the function:

- Input gray image
- Mapping array

$outputImage(r,c)=cdf(inputImage(r,c)+1);$

if $cdf(3) = 5$ then

if for some value say $(r,c)=(100,123)$, $inputImage(100,123)=2$ then

$outputImage(100,123) = cdf(inputImage(100,123)+1)$ ---→ Her we are adding one because our indexing starts from 1 and not from 0

$$= cdf(2+1)$$

$$= cdf(3)$$

$$= 5 \rightarrow \text{Equalized value}$$

With the intensity transformation, we are equalizing the histogram of the image. This means we are trying to adjust the contrast of the image by making sure the probability distribution of all pixels is as close to uniform as possible.

Example 1:

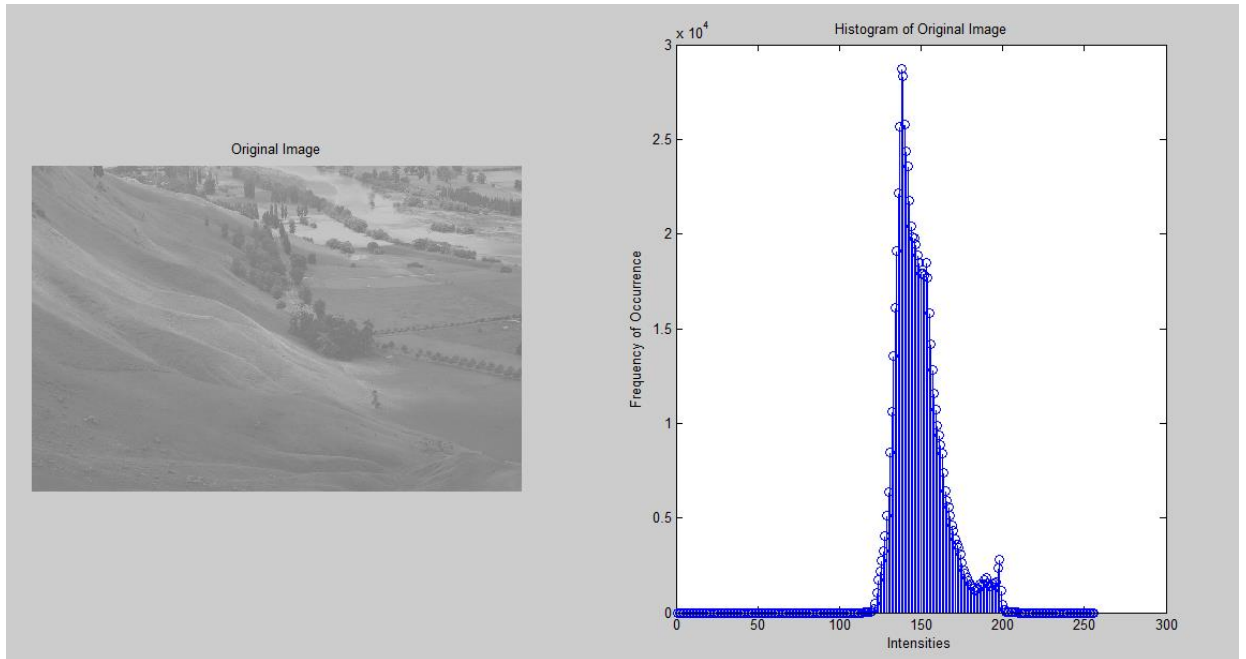


Figure 1

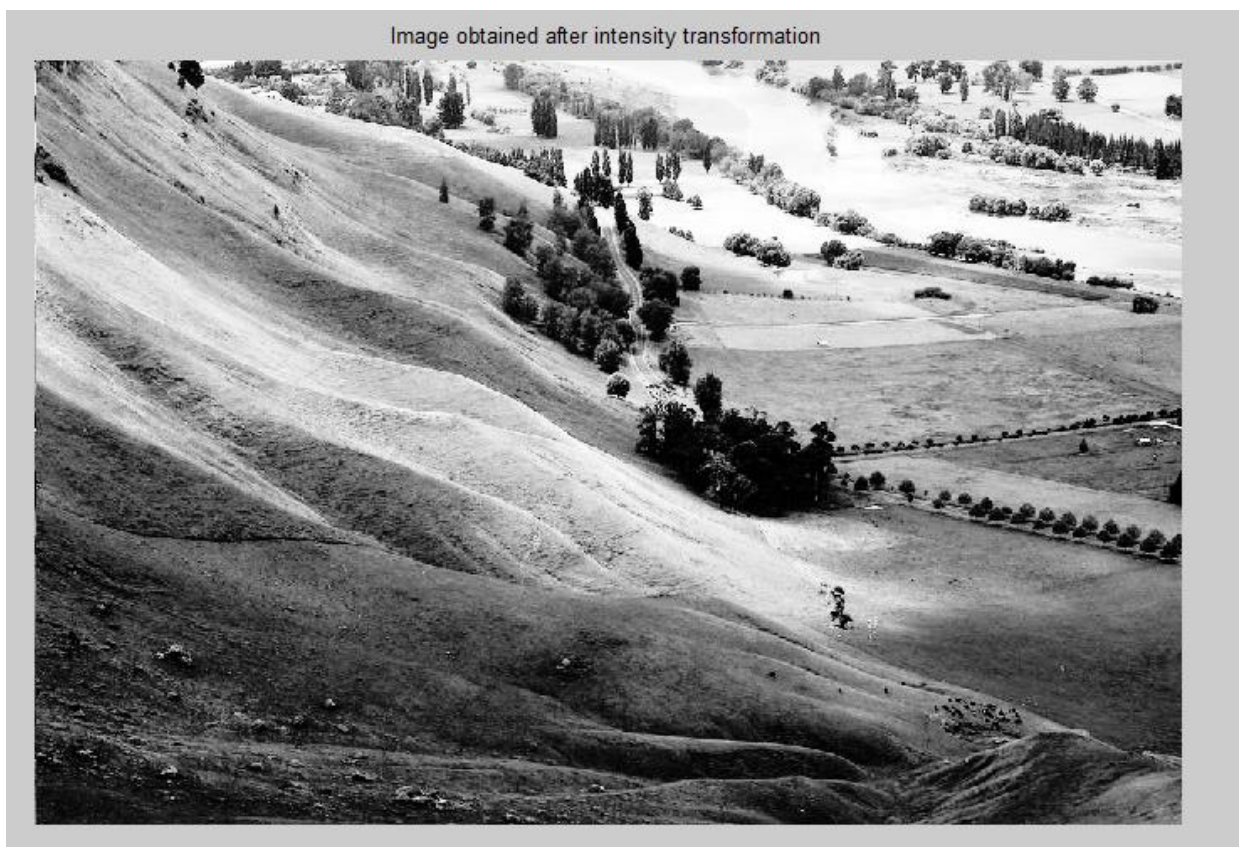


Figure 2

As we can see after applying the histogram equalization transform the image has become clear, as the intensities are spread out after equalization.

Example 2:

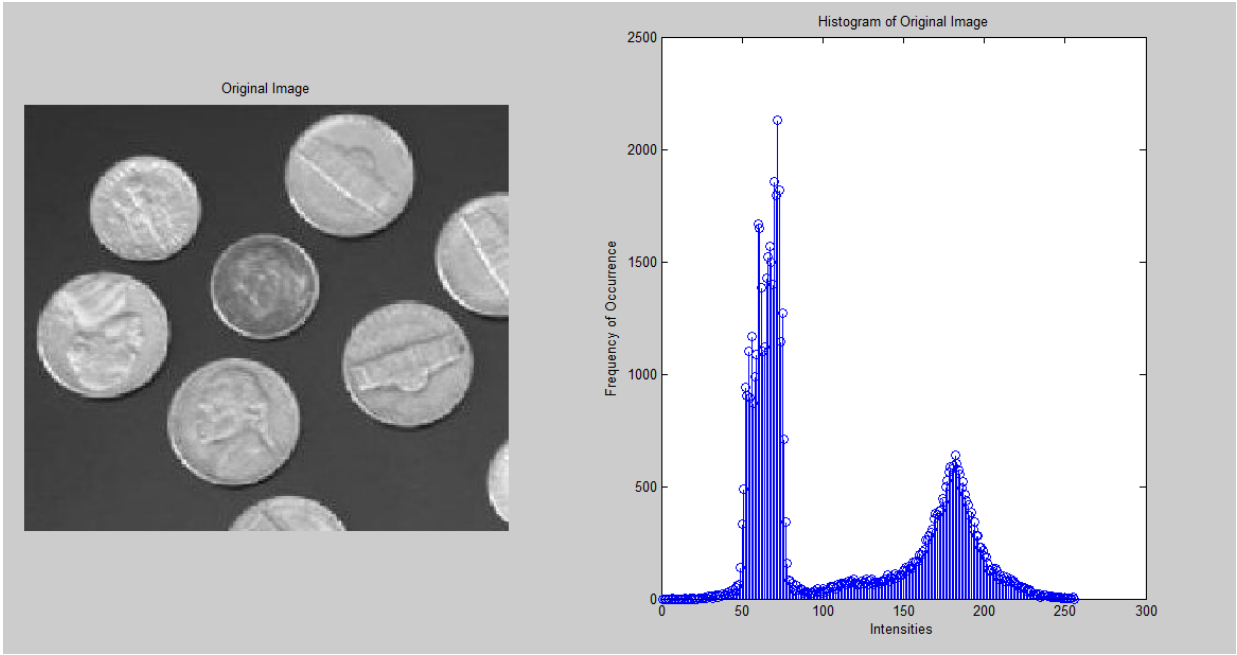


Figure 1



Figure 2

Example 3:

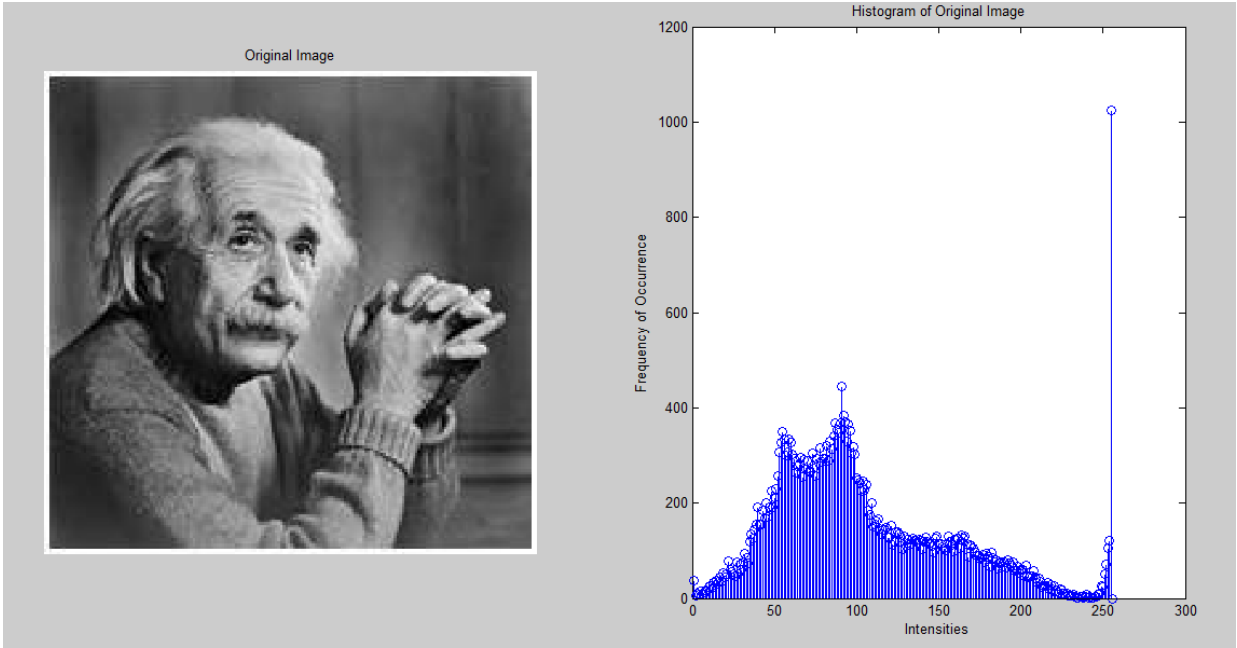


Figure 1

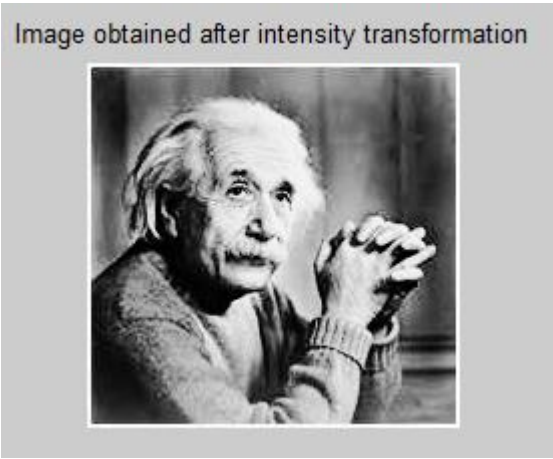


Figure 2

Example 4:

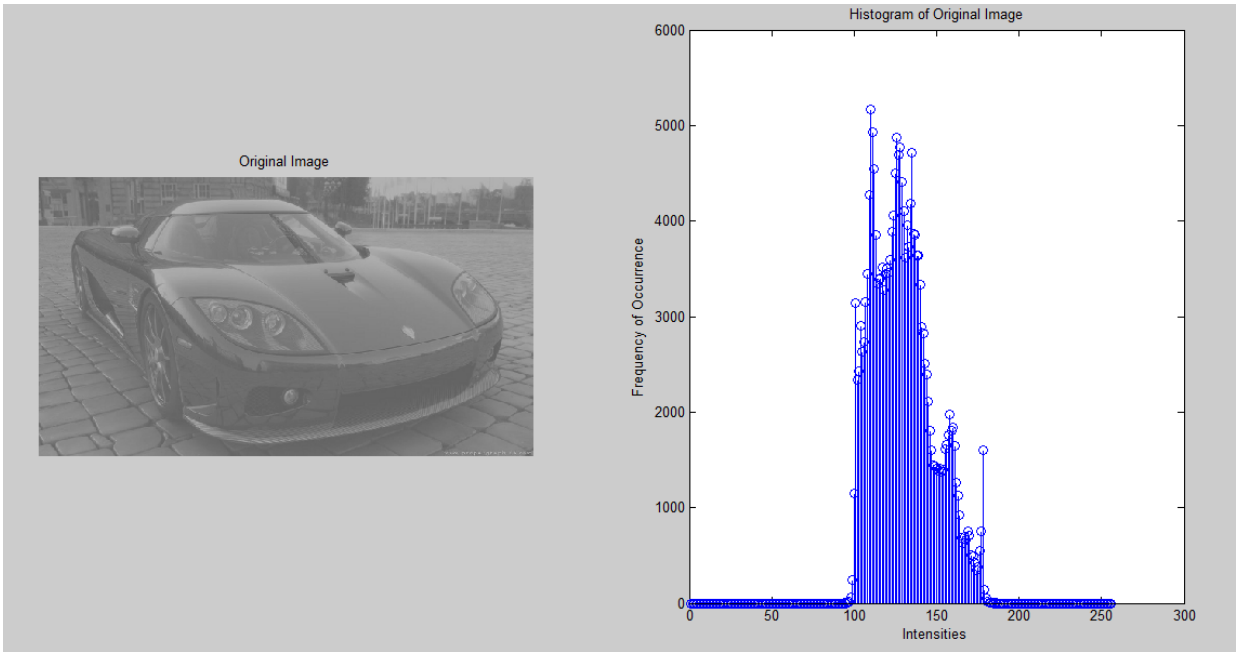


Figure 1

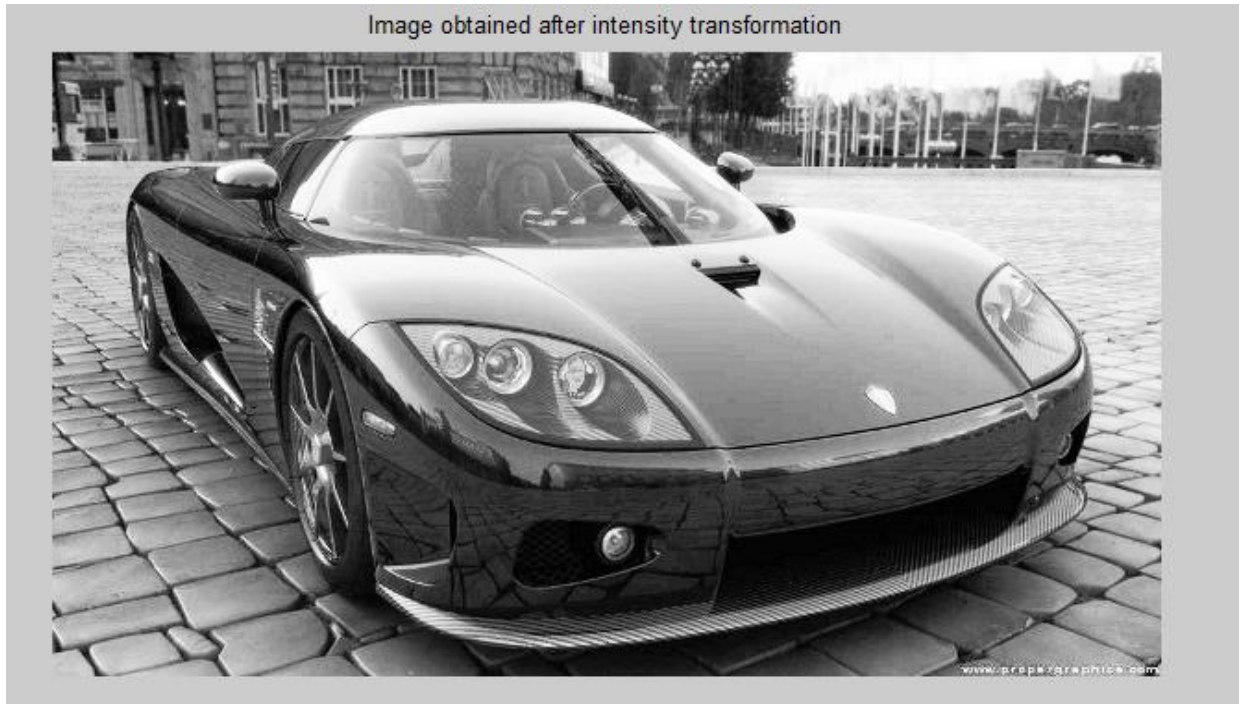


Figure 2

CODE: *iTransform.m*

3. An inverse histogram equalization transformation routine

For the inverse histogram equalization, the CDF (cdf1) of the image is calculated as mentioned in the description of the first function. Next, the CDF obtained is used to find the equalized image using intensity transformation. This results in equalized image. The CDF(cdf2) of equalized image is found. Now we map cdf2 to cdf1 and obtain the inverse transformation array. As a parameter of check, this inverse mapping is applied on the equalized image to check if the original image is returned.

Algorithm:

- i. Histogram calculation
- ii. Calculate pixel probability distribution
- iii. Calculate CDF-cdf1
- iv. Apply the intensity transformation of cdf1 on input image
- v. Calculate cdf2 for equalized image
- vi. Mapping cdf2 and cdf1 by checking the difference between each value of cdf2 with all values of cdf1
- vii. The index at which value of cdf1 gives the least difference is mapped with the corresponding cdf2 index

Example 1:

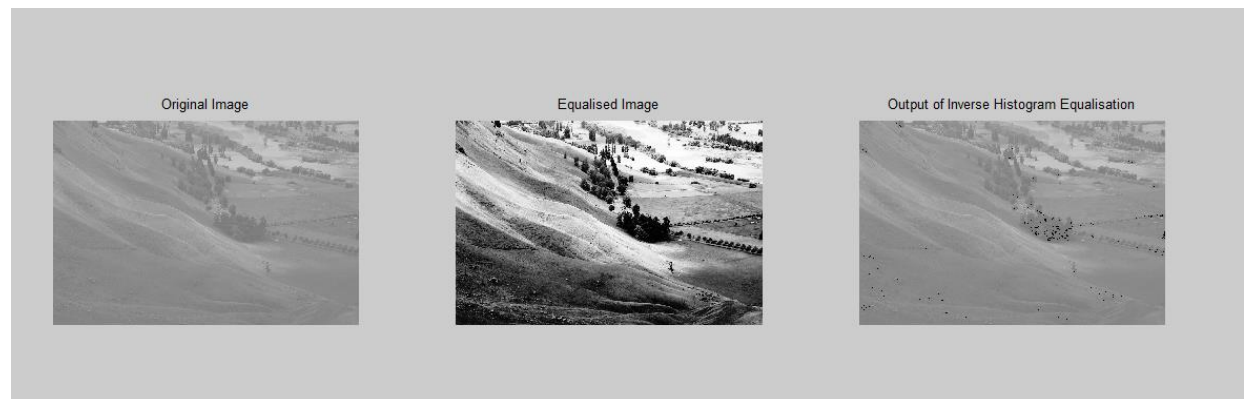
Mapping array is

0	123	124	125	126	127	127	128	128	129	129	129	129	130	130	130	131
131	131	131	131	132	132	132	132	132	133	133	133	133	133	133	134	134
134	134	134	134	134	135	135	135	135	135	135	135	135	135	136	136	136
136	136	136	136	136	137	137	137	137	137	137	137	137	137	138	138	138
138	138	138	138	138	139	139	139	139	139	139	139	139	139	140	140	140
140	140	141	141	141	141	141	141	141	141	142	142	142	142	142	142	143
143	143	143	143	143	144	144	144	144	144	144	144	145	145	145	145	146
146	146	146	146	146	146	147	147	147	147	147	147	147	148	148	148	149
149	149	149	149	149	149	150	150	150	150	150	150	151	151	151	151	152

```

152 152 152 152 152 152 153 153 153 153 153 154 154 154 154 154 155 155 155
155 156 156 156 156 157 157 157 157 158 158 158 158 159 159 159 160 160 160 160
161 161 161 162 162 163 163 163 164 164 165 165 166 166 167 168 168 169 170 170
171 172 173 174 175 176 178 180 182 184 186 188 189 191 193 195 196 197 208

```



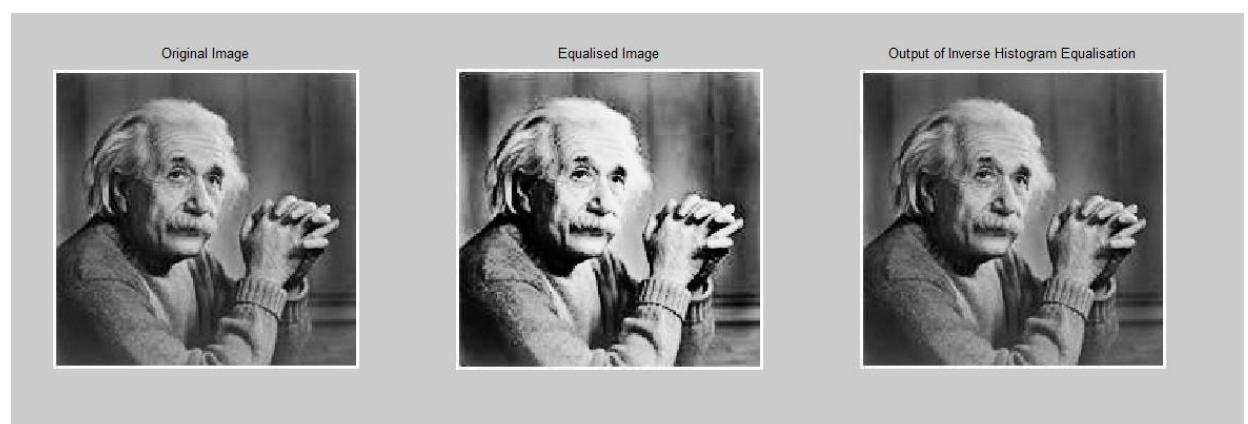
As we can see the image obtained after applying the inverse histogram equalization is same as the input image, which is as expected. The histogram equalization process is not purely reversibly, this can be seen with the granular black dots. This is because, while mapping we might not be able to map the values to the exact level and hence we map it to the nearest value which introduces small error.

Example 2:

```

Mapping array is 0  9 14 17 20 22 24 27 29 31 32 34 35 36 37 38 38 39 40
41 41 42 43 44 44 45 46 46 47 48 48 49 49 50 50 51 51 52 52 53 53 53
54 54 55 55 55 56 56 57 57 57 58 58 59 59 60 60 61 61 62 62 62 63 63
64 64 65 65 66 66 67 67 68 68 69 69 70 70 71 71 71 72 72 73 73 74 74
75 75 76 76 77 77 78 78 79 79 80 80 81 81 82 82 82 83 83 84 84 84
85 85 85 86 86 87 87 87 88 88 88 89 89 89 90 90 90 91 91 91 92 92 93
93 93 94 94 94 95 95 96 96 97 97 97 98 99 99 100 100 101 101 102 102 103
104 104 105 105 106 107 108 108 109 110 111 112 113 114 115 116 116 117 118 119
120 121 123 123 124 125 126 128 129 130 131 132 133 134 135 137 138 139 140 141
142 143 144 146 147 148 149 150 151 153 154 155 156 157 159 160 161 162 163 164
165 166 168 169 170 171 173 174 176 177 179 181 182 184 186 187 189 191 193 195
197 199 202 204 207 210 215 220 239 250 252 253 253 253 253 253 253 254

```



Example 3:

```

Mapping array is 0  0 0 0 1 1 1 2 2 2 2 3 3 3 3 3 4 4 4 4 4 4
5 5 5 5 5 5 5 6 6 6 6 6 6 7 7 7 7 7 7 8 8 8 8 8 8 9
9 9 9 9 9 10 10 10 10 10 11 11 11 11 11 12 12 12 12 12 13 13 13
14 14 14 15 15 16 16 17 17 18 19 20 21 22 23 24 26 27 29 30 31 32 33
34 35 36 37 37 38 39 40 40 41 42 43 43 44 45 46 47 48 49 50 51 52 53

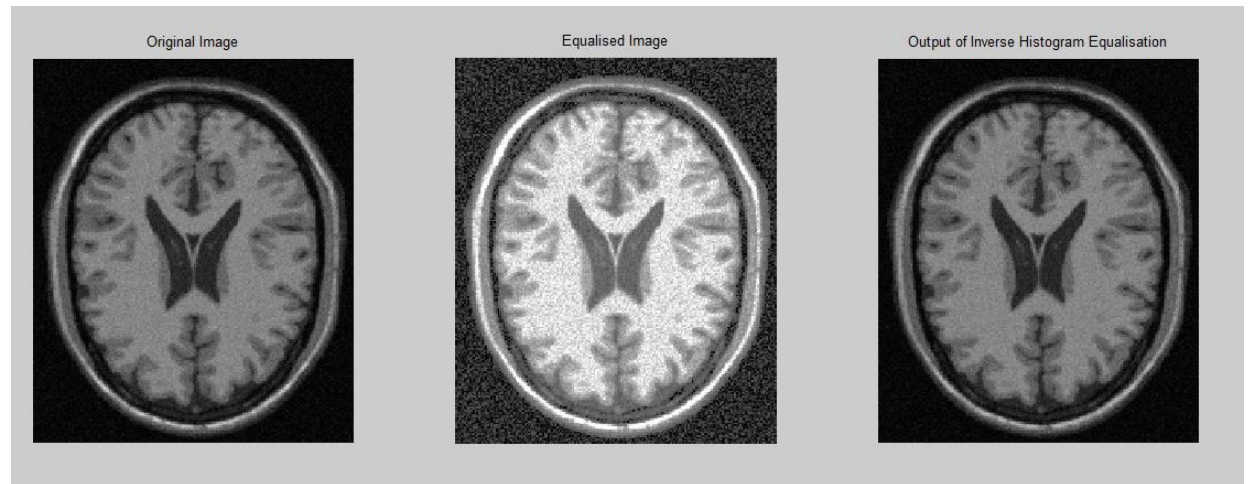
```



```

55 56 57 59 61 63 65 67 69 71 73 74 76 78 79 81 82 83 84 85 86 87 87
88 89 89 90 91 91 92 92 93 93 94 94 95 96 96 97 97 98 98 99 99 100
100 101 101 102 102 103 103 104 105 105 106 107 107 108 109 110 111 112 113 113
114 115 116 117 118 119 119 120 121 121 122 122 123 123 124 124 125 125 125 126
126 126 127 127 127 128 128 128 129 129 129 130 130 130 130 131 131 131 132 132
132 133 133 133 133 134 134 134 135 135 135 136 136 136 137 137 138 138 139 139
140 140 141 142 142 143 144 146 147 150 157 175 222

```



CODE: *inversehistogram.m*

4. Color matching

As described in the requirements, two images are taken as input. First image is the gray scale image which is to be colored and the second is the reference color image. The normalized histogram(cdf) of the gray scale image is mapped with normalized histogram of the RGB layers of the color image and 3 different mappings arrays are created. These three mapping are applied on the gray image and a new color image is obtained from them.

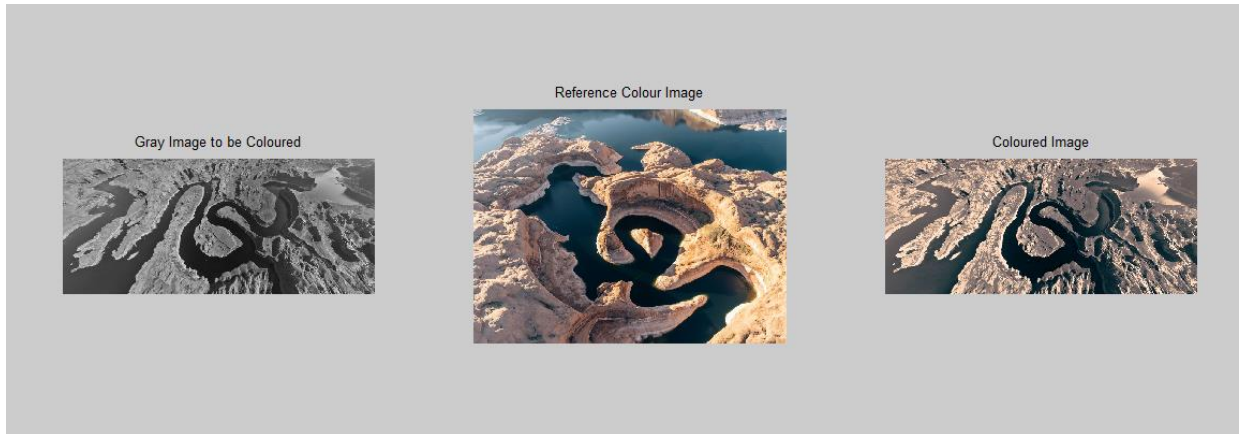
The function has following inputs:

- Input gray image
- Reference colour image

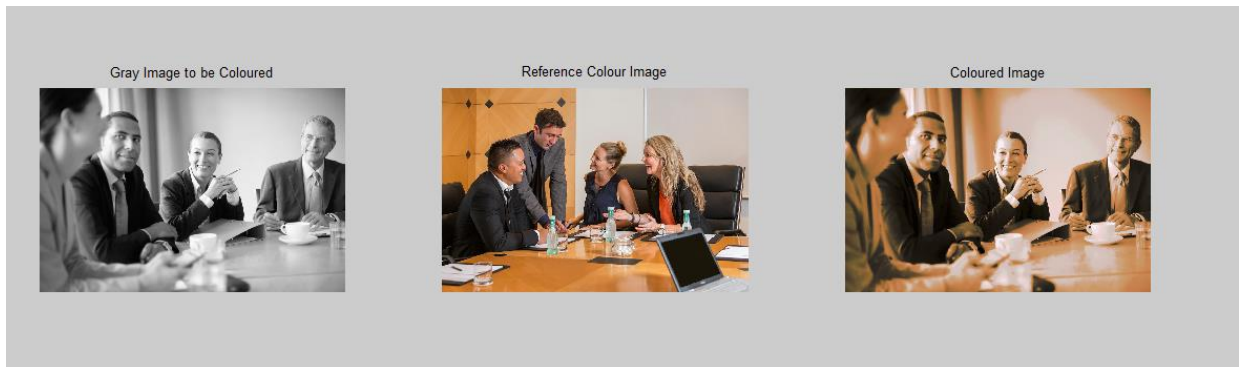
Algorithm:

- i. Calculate histogram of input gray image – H1
- ii. Calculate histogram of all three planes of color image – R, G,B
- iii. Map H1 and R and find the intensity transformation array MapR
- iv. Map H1 and G and find the intensity transformation array MapG
- v. Map H1 and B and find the intensity transformation array MapB
- vi. Apply MapR, MapG and MapB on the input image and obtain 3 new planes of the coloured image. For applying the mapping use the same steps as mention in intensity transformation function.
- vii. Combine all three new transformed planes to obtain coloured image.

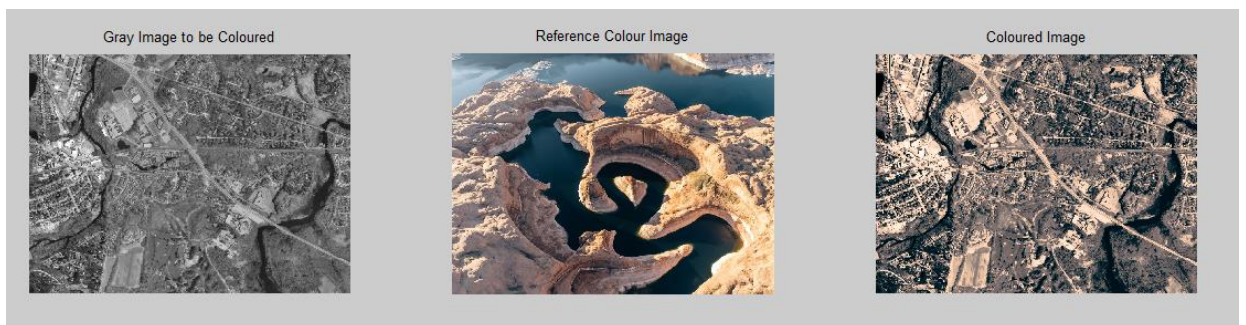
Example 1:



Example 2:



Example 3:



Example 4:



Here two images from different context are used.

CODE: *colour.m*

B. Counting cells

1. Otsu's thresholding method

As per the requirements, a function to threshold the image using Otsu thresholding method has been implemented. Following the algorithm, the image is progressively divided into two groups and the probability distribution of these group of pixels P1 and P2 is calculated. The mean values of these two sets of pixels are calculated and iteratively it is checked to find which set of pixels give the maximum variance. The value of pixel at which maximum variance is calculated is taken as the threshold value and image is thresholded.

Example 1:

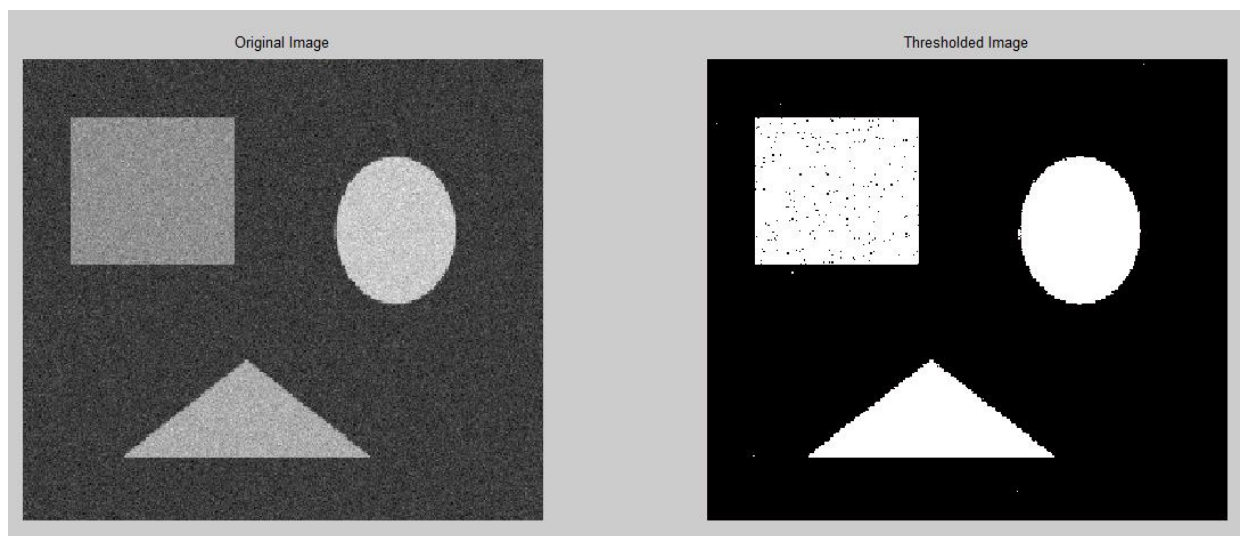


Figure 1

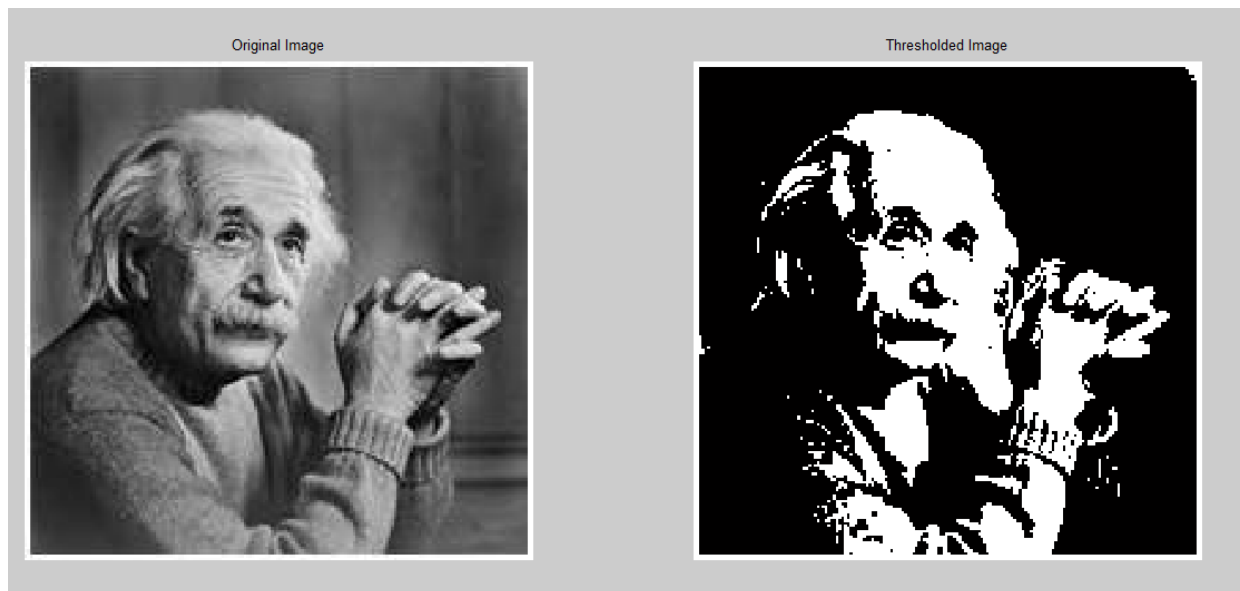


Figure 1

Example 3:



Figure 1

CODE: *otsuThresh.m*

2. Adaptive thresholding method

The image is divided into multiple blocks of size *bsize* and analysed with reference to the input minimum variance, to find the threshold of each block. The mean of all the pixels in the block is calculated and then the variance of each block is calculated. The blocks which have variance greater than minimum variance are foreground pixels and hence are thresholded at a level mean plus one standard variance.

Example 1:

Block size: 100

Minimum variance value : 4.6



Zero padding has been done at the borders so that the image is equally divided in to the block size.

Example 2:

Block size: 10

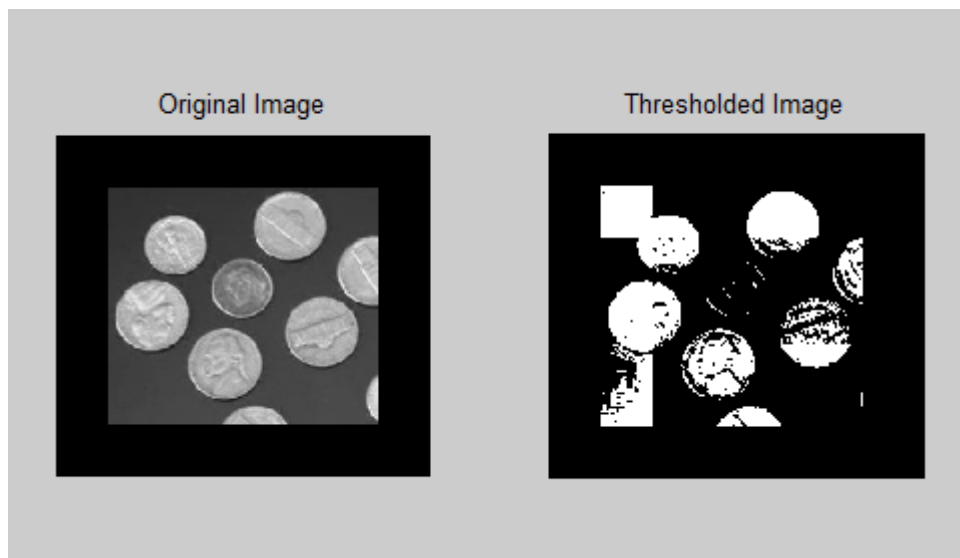
Minimum variance value : 0.002



Example 3:

Block size: 100

Minimum variance value : 2



Some noise can be seen when we use adaptive thresholding , since it looks at the image at a block level to identify the threshold.

CODE: *adaptive_Thresh.m*

3. Cell Detection

In this part, Otsu's thresholding and adaptive thresholding methods are used to identify the cells in the given image. The thresholding algorithms are followed by topological denoising to get an appropriate count.

CODE: *cellDetectOtsu.m*

Cell detection using Otsu's thresholding method results:

>>Number of cells

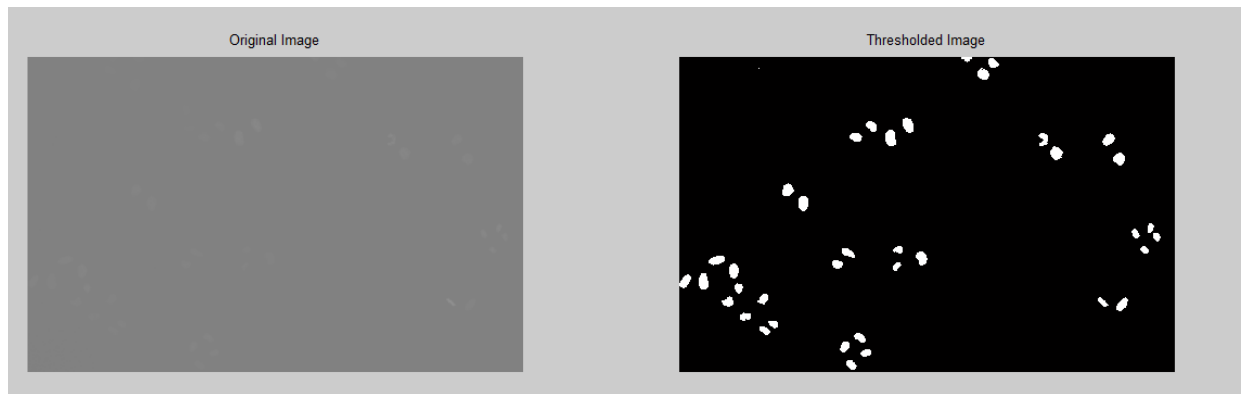


Figure 1

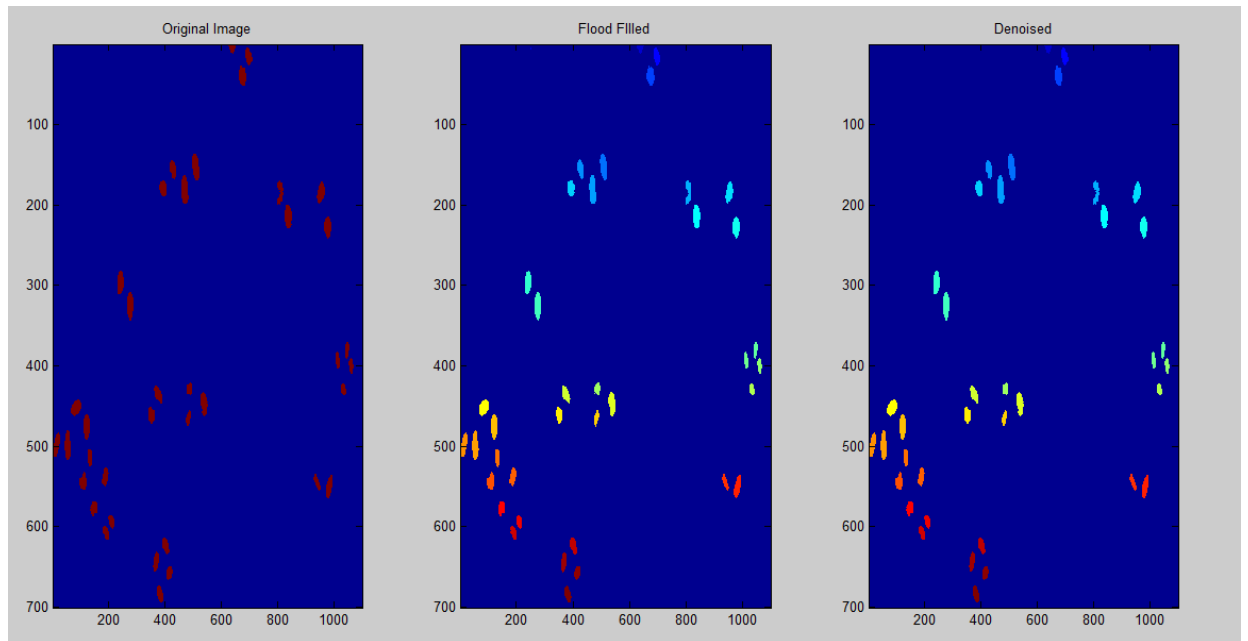


Figure 2

CODE: *cellDetectAdap.m*

Cell detection using adaptive thresholding method results:

Block size: 65

Minimum variance value: 0.563

```
>>Number of cells
55
```

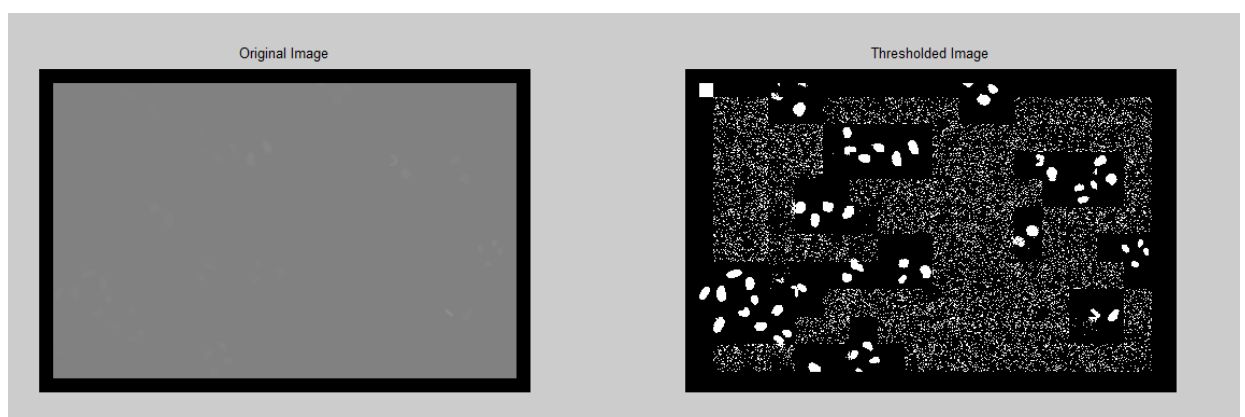


Figure 1

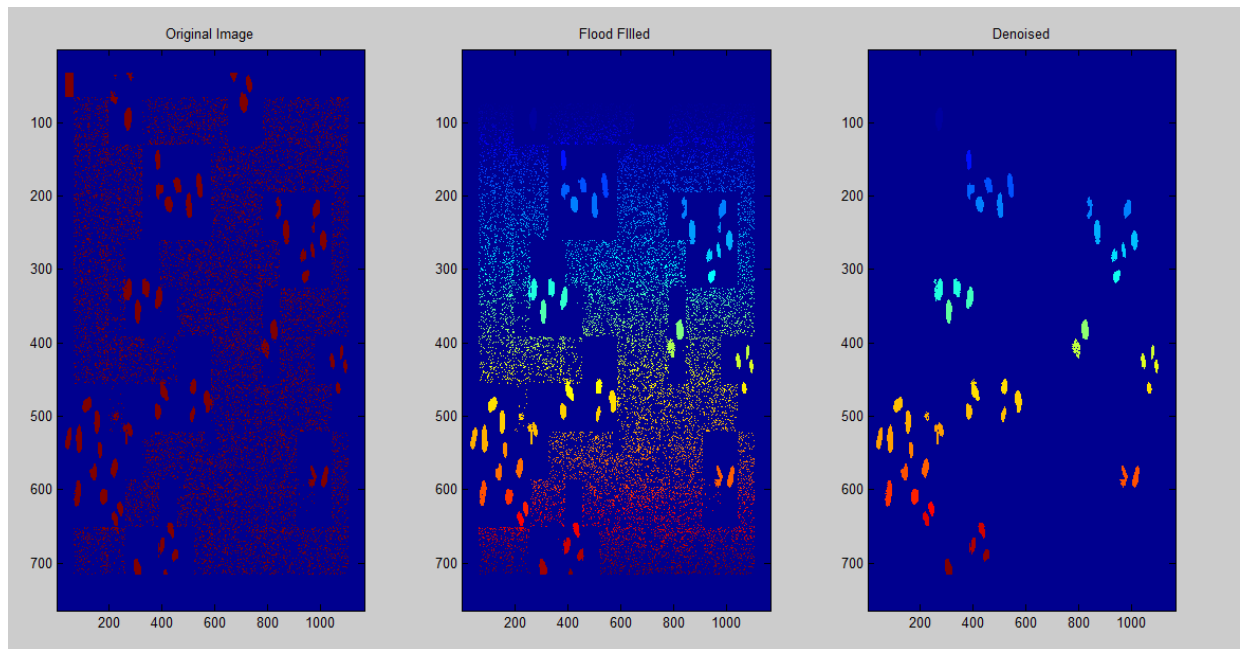


Figure 2

Analysis:

- As we can see using Otsu's method, the global threshold is used and with adaptive thresholding, each block has a different threshold i.e. ., it is local threshold
- With adaptive threshold, using the local threshold a lot more details are uncovered as compared to global thresholding.
- Cell Count with adaptive thresholding is much accurate as compared to Otsu.
- Global threshold works well when the image does not have large variations in the intensity level.
- When adaptive thresholding is used, we can see a lot of noise. This is eliminated by using topological denoising algorithm.