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A. Part 2

Image test1.bmp is a grayscale image that appears to have been taken under poor lighting conditions, rendering it being underexposed with many details of the image being lost in its darker regions. The image is also observed to be contaminated with gaussian noise, however because the image is underexposed it is not immediately obvious on first glance.

Running improfile(I,[1,363],[25,25]) returns Fig. 1, which describes the image profile along pixels 1 to 363 on the x-axis and along pixel 25 on the y-axis. The image profile line can be observed as the red line in Fig. 2. We can observe that the peaks and valleys in the plot correspond to the bright and dark regions of the image, respectively. In the flatter regions of the plot, in the ranges x = [124, 260] and x = [294, 368], we can observe a lot of small fluctuations in intensities, which can be attributed to the image being contaminated with a lot of gaussian noise.

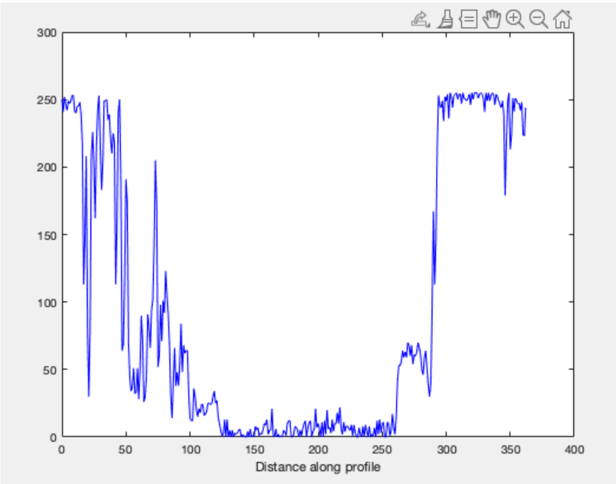

Fig. 1. improfile plot along x = [1,363], y = 25

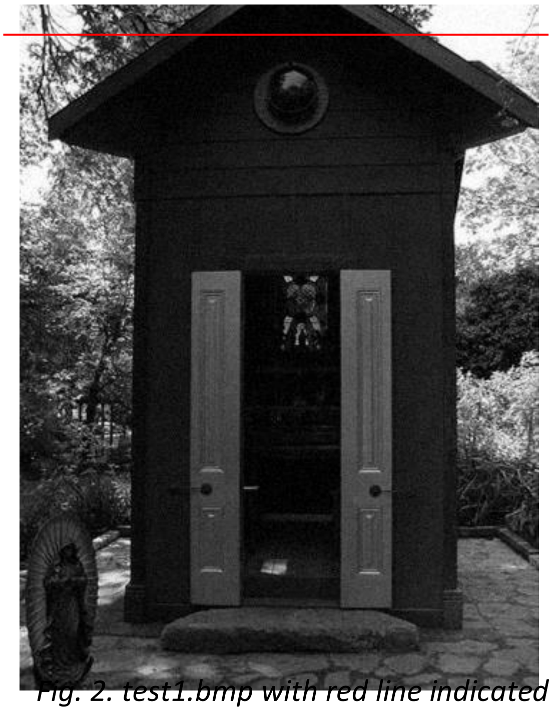

Fig. 2. test1.bmp with red line indicated region of improfile plot

A. Part 3.

Plotting the histogram of the image with imhist(I), (Fig. 3) we observe that the distribution of gray levels is heavily skewed towards the left, confirming our suspicion that the image is underexposed. There is also evidence of clipping on both 0 and 255 as observed from the image's histogram (Fig. 3). This could be a result of inappropriate image processing methods or due to very light salt and pepper noise. There are primarily 3 observable peaks in the histogram plotted, which correspond to the gray levels of 23, 67 and 248 respectively. We are able to make use of imtool Adjust Contrast function, displaying only a certain range of gray levels of the image in order to ascertain which segments of the images corresponds to which peak. The first peak at the gray level of 23 corresponds to the dark walls of the building (Fig. 4), the second peak at gray level of 67 (Fig. 5) corresponds to the doors of the building and the flooring, as well as the outlines of some of the trees and branches while the third peak at a gray level of 248 (Fig. 6) corresponds to the skies at the top corners of the image.

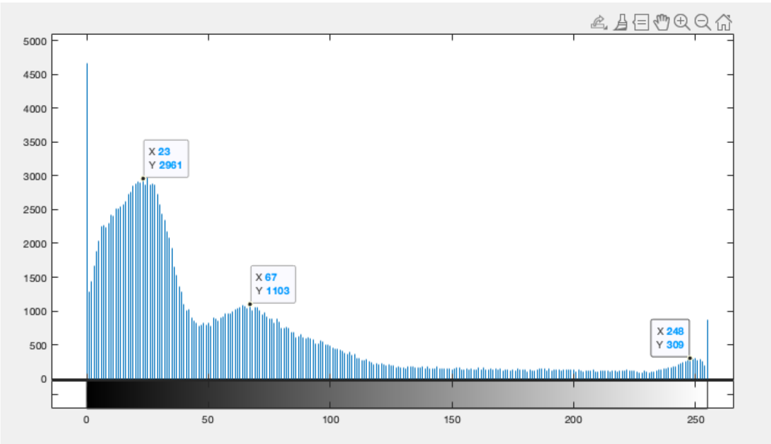

Fig. 3. test1.bmp Histogram Plot

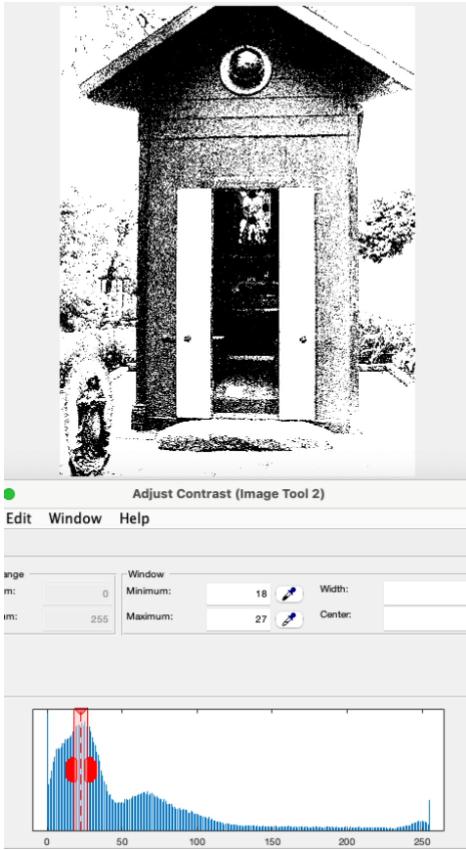

Fig. 4. test1.bmp First Histogram Peak

Fig. 5. test1.bmp Second Histogram Peak

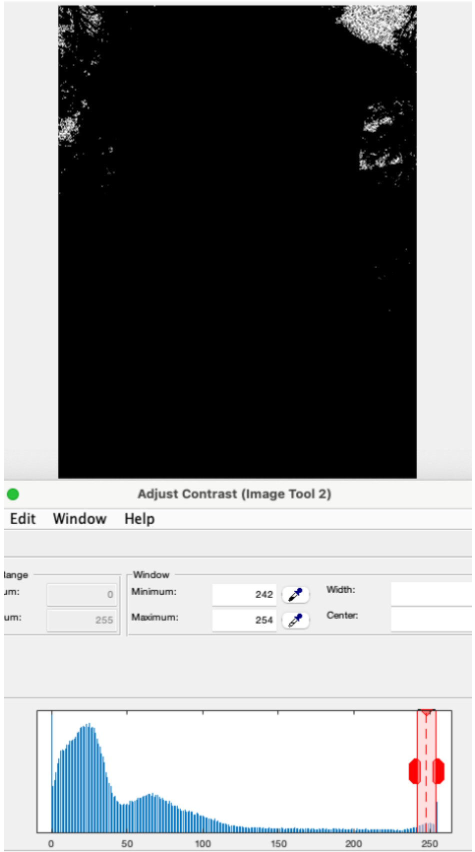

Fig. 6. test1.bmp Third Histogram Peak

A. Part 4

We use Matlab's histeq (histogram equalisation function) to try to enhance the contrast of our image by remapping intensity values and stretching out the intensity range of the image. The function that was used tries to match the image's histogram approximately to that of a flat histogram with 255 gray intensity levels.

The result of this is an image (Fig. 7) that has its intensities remapped, with the image's new histogram given by Fig. 8. We are able to observe certain details of darker regions of the image that were not apparent earlier, such as some details of the interior of the building and the statue in the bottom left corner. However, it is not a vast improvement from the original image because we also lost many details of the original image from its brighter regions, such as the trees in the background. This happens because the histogram equalisation function simply tries to match the image's histogram to that of a flat one, and since most of the intensities of the original image's histogram are congregated in the darker regions, a lot of these low grayscale intensity pixels were remapped to higher intensity ones, while some of the higher grayscale intensity pixels (brighter regions) were all mapped to a new level that is even higher. Therefore, the darker regions of the original image are salvaged but the brighter regions become overexposed, thereby HE to a flat histogram is not the best image processing method to improve the image in this case. A slightly more appropriate method could be Adaptive Histogram Equlisation, which computes several histograms to enhance contrast in distinct regions of the image – an example could be segmenting the building and flooring to one region (darker region), and the background trees and skies could be another region (brighter region).

Additionally, applying histogram equalisation before de-noising resulted in increased contrast of the image gaussian noise, and thus the gaussian noise is now more apparent than before. To improve the result of this technique, we could first perform smoothing on the image by means of a mean or median filter to denoise the image.

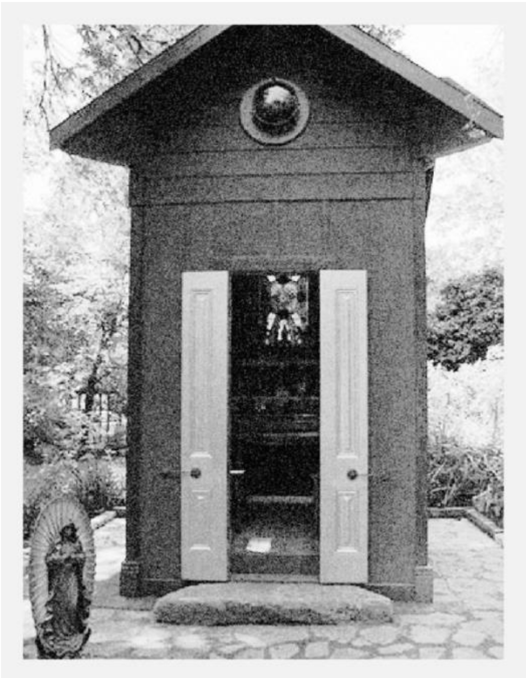

Fig. 7. test1.bmp after Histogram Equalisation

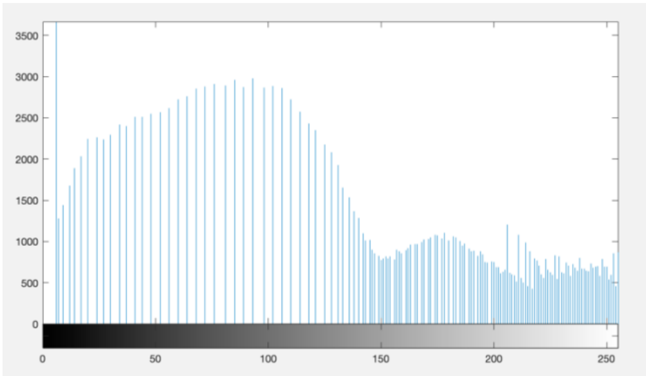

Fig. 8. Histogram of test1.bmp after Histogram Equalisation

B. Part 3

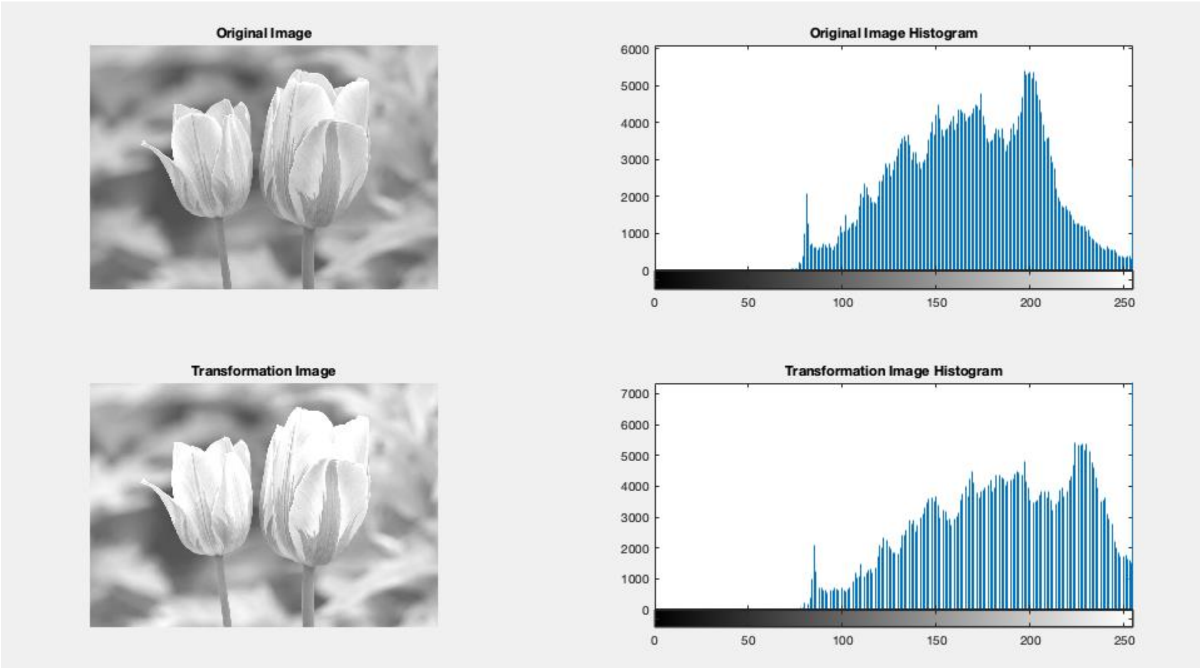

Fig. 9. test2.bmp image Before and After applying transformation T, with a = 1.2, b = -10

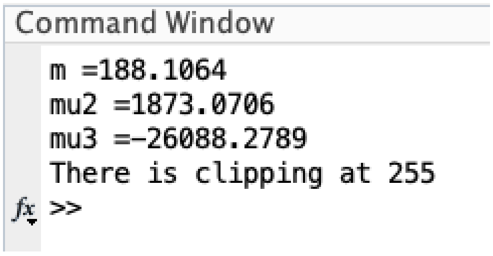

Fig. 10. m, mu2, mu3 and Clipping Output of test2.bmp image after applying transformation T, with a = 1.2, b = -10

B. Part 4

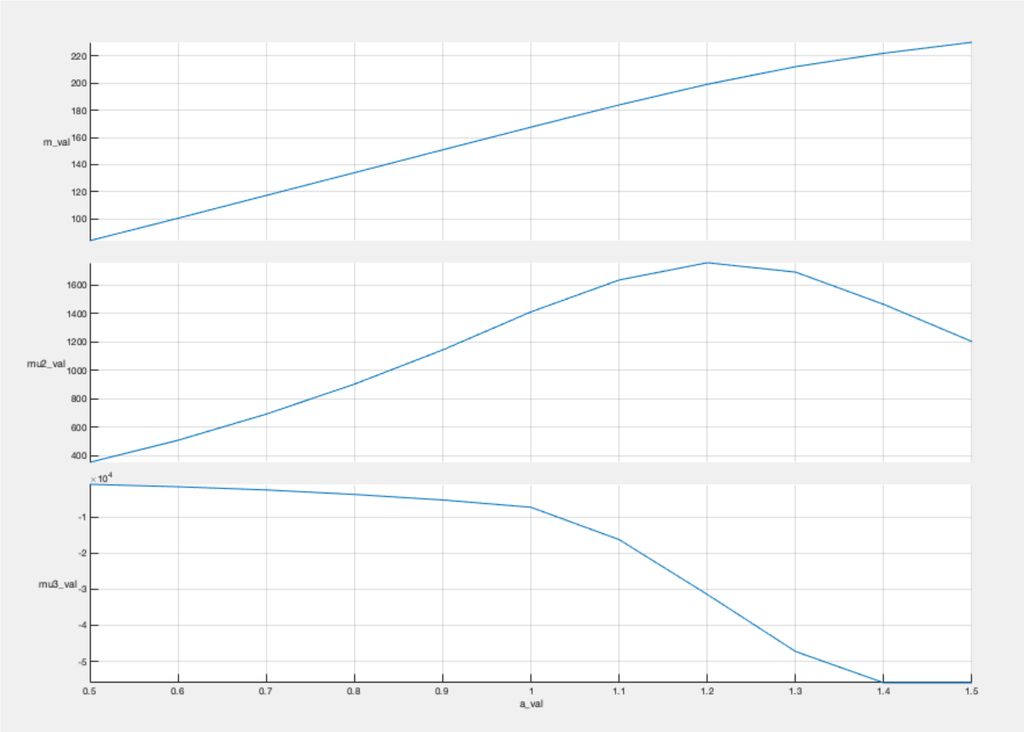

Fig. 11. Plot of a = [0.5, 1.5] against m, mu2, mu3

1 a_val	2 m_val	3 mu2_val	4 mu3_val
0.5000	84.0518	353.2476	-898.6275
0.6000	100.5611	508.4035	-1.5625e+03
0.7000	117.3507	692.5718	-2.4433e+03
0.8000	134.0817	903.7772	-3.7010e+03
0.9000	150.8983	1.1442e+03	-5.2304e+03
1	167.6004	1.4123e+03	-7.2537e+03
1.1000	183.9521	1.6368e+03	-1.6222e+04
1.2000	199.1632	1.7583e+03	-3.1452e+04
1.3000	212.1010	1.6923e+03	-4.7271e+04
1.4000	221.9870	1.4651e+03	-5.5952e+04
1.5000	230.0611	1.2034e+03	-5.5932e+04

Fig. 12. Table of Values for m, mu2, mu3 for a = [0.5, 1.5]

Overall, as the value of *a* increases, the overall brightness of the image increases, as we observe from the images of test2.bmp in Fig. 13 and Fig. 14 when a is 0.5 and 1.5, respectively. This is expected because when b = 0 in the transformation function specified, for values of *a* < 1 the transformation will return an image with intensity values multiplied by the factor of *a*, which is a fraction of the original intensity when *a* < 1, hence the intensities are lowered. The original intensity values of the pixels are returned when *a* = 1. When *a* is increase to values >1, the intensity values of the image will correspondingly scale up to values greater than the original image intensity value, thus returning us with a brighter image than the original.

Fig. 13. Transformed image at a = 0.5

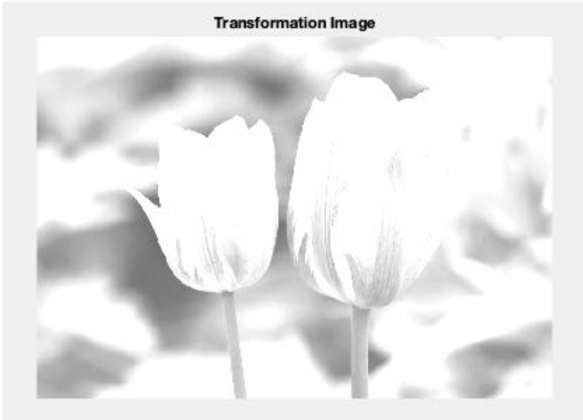

Fig. 14. Transformed image at a = 1.5

m, the mean of the intensity values increases with increasing values of a (Fig. 11). In particular, for a = 0.5, we find that the mean intensity of the image is approximately half that of the value of the mean when a = 1, as we can also observe from the table in Fig. 12. Correspondingly, the value of the mean intensity at a = 1.5 is also approximately 1.5 times of the mean when a = 1. The most notable observation we can make is that when a is set to values >1, the mean intensity of the image increases at a decreasing rate, which we observe in the slowed increase of the graph past a = 1. Correspondingly when observing the transformed image at values of a > 1, we observe that the image already starts losing many of its details in its brighter regions. This is attributed to clipping at intensity value 255 when a is set to values >1. Values increased to that of greater than 255 from the multiplication factor >1 are clipped to the value of 255.

mu2 corresponds to the variance of the intensities, or the squared of the standard deviation. We observe that the variance of the image intensities increases as a increases, peaks at a = 1.2, then decreases again (Fig. 11). Inspecting the histogram at a = 1.1 (Fig. 15), we observe that the histogram largely preserves its shape. At a = 1.2 (Fig. 16), the peak of the histogram distribution has not yet been clipped off, while at a = 1.3 (Fig. 17), the peak of the histogram distribution has been clipped at intensity 255. This explains the phenomenon because at the value of a = 1.2 where the peak of the histogram is just about to be clipped off, the standard deviation and hence variance of the intensities will peak because there still remains a large amount of intensity values that has yet to be clipped, many with high intensity values as well, pushing up the standard deviation and variance of the intensities when these high intensities are compared against the long left tail of the histogram. Finally at a = 1.3, when the peak of the histogram has been clipped to intensity 255, a large number of pixels will have the intensity of 255, hence lowering the standard deviation and hence variance of the intensities. We also observe in the transformed image of a = 1.3 (Fig. 18) that many regions of the image have become overexposed and many details have been lost in the regions of high intensities.

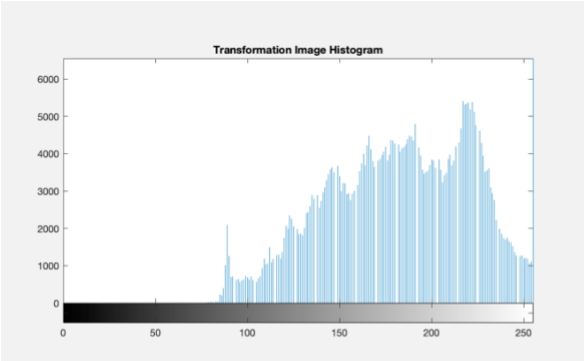

Fig. 15. Histogram at a = 1.1

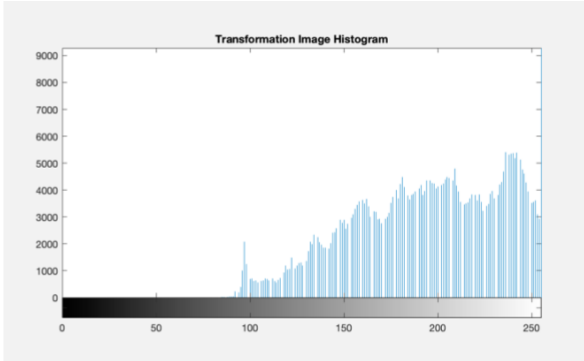

Fig. 16. Histogram at a = 1.2

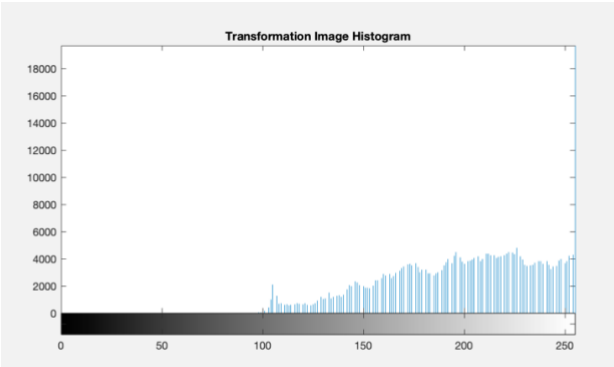

Fig. 17. Histogram at a = 1.3

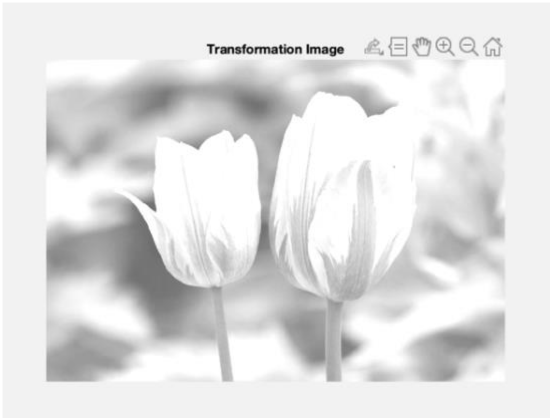

Fig. 18. Transformed Image at a = 1.3

mu3 corresponds to image skewness, which deviates from 0 as the histogram distribution deviates further away from a normal distribution (Fig. 11). The skewness of the image is negative for all values of a in the range [0.5, 1.5]. This is the case because when we look at the histogram in cases of *a* = [0.5,1] where the image experiences no clipping from the transformation, the left tail of the histogram is always longer and flatter with respect to the highest intensity peak point. In the cases of *a* = [1.1,1.5], clipping occurs and in the most extreme case where *a* = 1.5 (Fig. 19), we only see the left tail of the histogram while the right tail is completely clipped off.

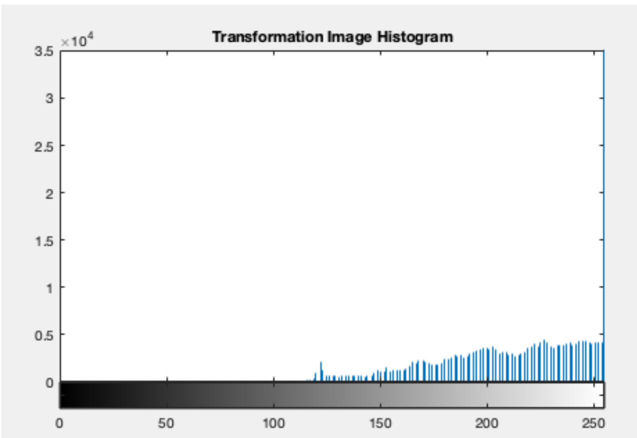

Fig. 19. Transformed Image at a = 1.5

B. Part 5

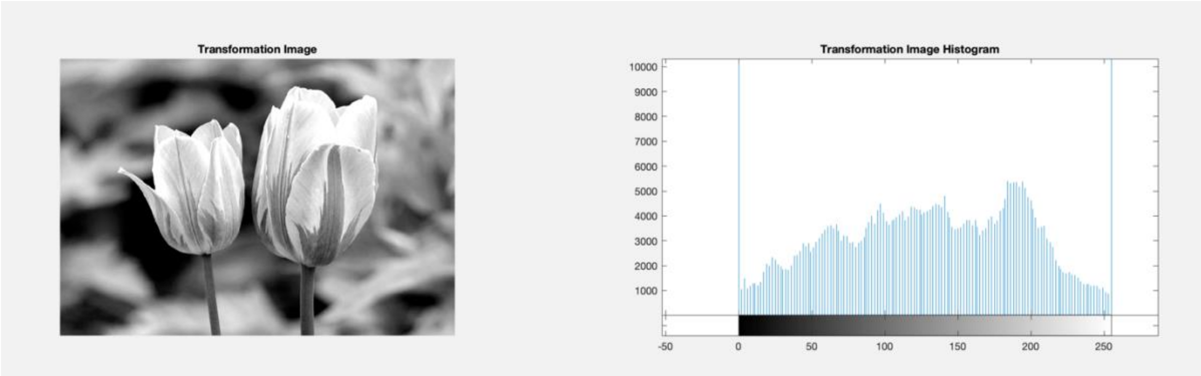

Fig. 20. Solution 1: Transformation Image and Corresponding Histogram at a = 1.9, b = -100

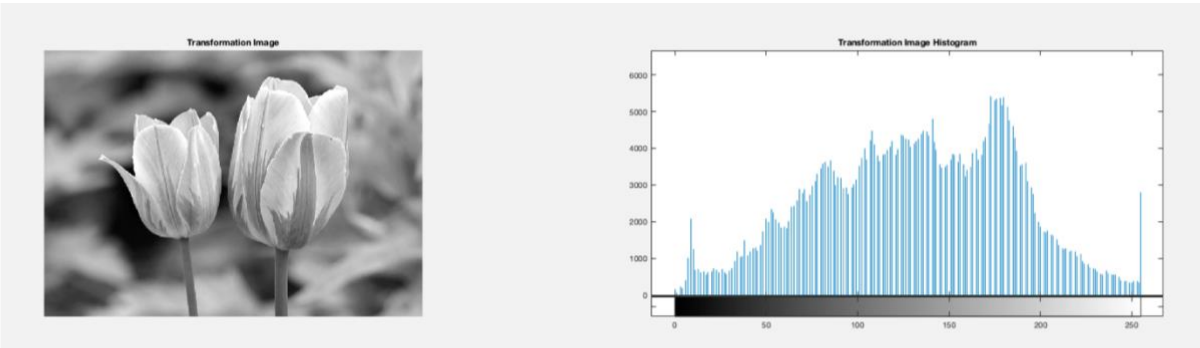

Fig. 21. Solution 2: Transformation Image and Corresponding Histogram at a = 1.41, b = -75

Best image is obtained when *a* = 1.9, b = -100 (Solution 1).

I found that adjusting b had the effect of translation on the histogram, with the translation amplified by the factor of *a*. Decreasing the value of b left-shifted the histogram while increasing the value of b right-shifted the histogram.

Adjusting the value of a had the effect of "stretching" the histogram, whereby increasing the value of *a* > 1 will stretch the histogram to become "fatter" and decreasing the value of *a* to < 1 had the effect of making the histogram "skinnier".

In finding the optimal *a* and b values, I could choose to enhance contrast of the image by increasing a and decreasing b, while sacrificing some pixels at the extreme low and high intensities of the image due to clipping (Solution 1, Fig. 20). I could also choose to improve the image by just observing the histogram and aiming to preserve the portions of the histogram where the densities of the intensities were non-negligible, while also minimizing clipping at the intensity 255 (Solution 2, Fig. 21). In fact, in Solution 2, there is no clipping reported at 0, while only minimal clipping occurs at 255. This guarantees that all details of the brighter regions of the image are preserved.

However, I chose the former solution, Solution 1, of sacrificing pixels at both ends due to clipping at both 0 and 255. Even though the amount of clipping is a lot more significant as compared to solution 2, I observed from the image that a lot of the pixels with clipped intensities do not contain crucial information to the viewer. For example, many clipped pixels at intensity 0 caused almost no details in the dark regions of the background to be lost. Similarly, many clipped pixels to intensity 255 forms the brighter regions of the petals on the flower on the right (see Fig. 20), however the fine details of the petals are still very much observable and no details seem to have been lost. In fact, boosting the contrast in this way actually greatly improved the appeal of the image, since the now highly contrasted image allows us to observe the finer patterns on the petals more clearly, since there are several dark gray regions on the petals as well. The focus of the image is clearly on the flowers, hence the clipped regions at 0 do not really matter.

In order to improve the outcome of the image, I thought of making adjustments to the transformation function. The following adjustment to the transformation function was based on the theory that contrast can be boosted by spreading brightness away from the mean intensity value.

s_k = a*(r_k - b) + b   (1)

With the function described in (1), I thought that by replacing b with the image mean of the original image, calculated to be 167.6004, I would be able to effectively boost contrast by setting a to a value > 1. However, the results were hardly what I expected (Fig. 22)

Fig. 22. Transformation Image and Corresponding Histogram at a = 1.1, b = 167.6004

Substituting smaller values of b also did not produce satisfactory results, with the output image being largely similar in visual quality as compared to the original image. This was because upon research, I found that the above function only effectively boosts image contrast in an RGB image, where we perform the above function on R, G and B intensities separately, for every pixel.

Moving on, I thought about how determining the optimal a and b could be improved mathematically. For a chosen a value, we could perhaps determine the range of intensities to be kept and to be clipped through the mu2 value calculated. Since mu2 corresponds to variance, we could take its root to obtain the standard deviation. Based on the calculated mean value for each input a value, we could only choose to include the gray level intensities that correspond to 2 standard deviations away from the mean. That way, we are able to permit a small range of intensities from being clipped, without having to visually observe every image that we choose to process in this way. The limitation to this method is that the histogram distribution has to conform as closely as possible to a normal distribution, which in the case of this image, seems appropriate to perform on. If the image histogram closely conforms to a normal distribution, we can confidently say that less than 5% of the total pixels will be clipped to 0 or 255, since we chose to include intensities 2 standard deviations from the left and right of the mean of the normal distribution.

I also thought about how to improve the image output by better accentuating the details of the darker regions of the image, while also improving image contrast. To do this, I performed histogram specification on the image with the target distribution of the Histogram as in Fig. 23.

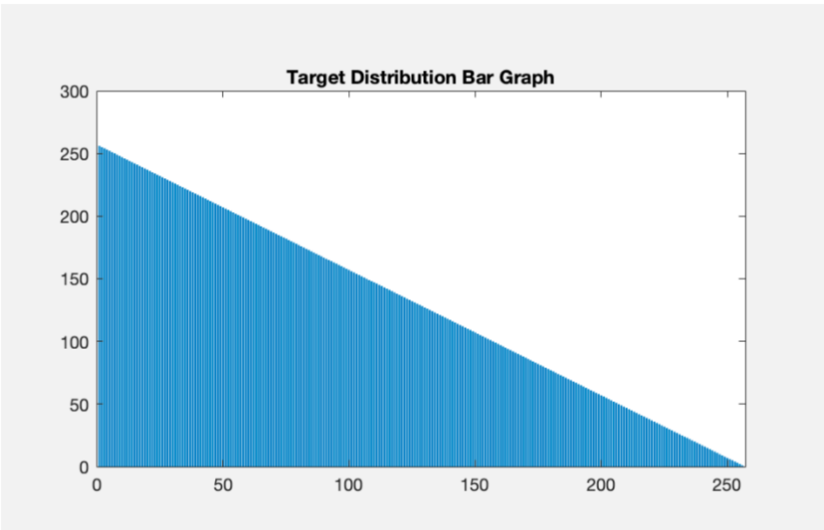

Fig. 23. Target Distribution plot of Histogram Specification

The result of this is an image with the finer details within the bright regions of the petals being recovered (fine dark lines on the petals). Whereas we cannot observe these details in the image previously simply using Histogram Equalisation, with Histogram Specification using the specified target distribution, we perform equalisation of the original histogram while making it conform to the shape of the target distribution, and we are able to recover the aforementioned details (Fig. 24 vs Fig. 20). As observed in the resultant histogram in Fig. 25, the darker regions of the image are accentuated by bumping up their intensity, and the overall intensity range of the image is also stretched out. The result of bumping up the intensity levels of the lower intensity gray levels and at the same time, suppressing the intensity levels of the higher intensity pixels of the image, is that the fine dark gray lines which form the petal details in the brighter region of the image (flower on the right) are more prominent.

Fig. 24. Image after Histogram Specification

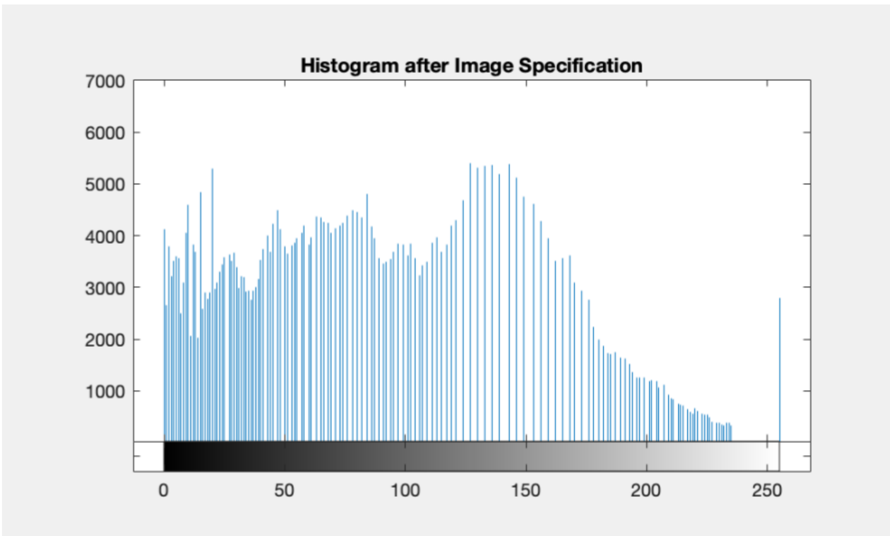

Fig. 25. Histogram after Histogram Specification

B . Part 6

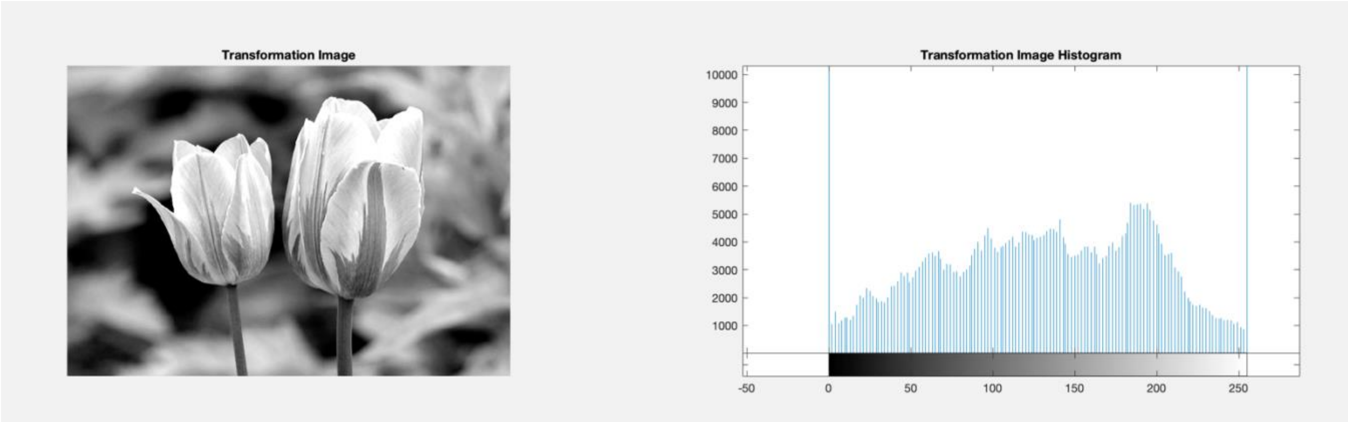

Fig. 26. (Repeat of Fig. 20.) Best Image after Transformation function and corresponding Histogram

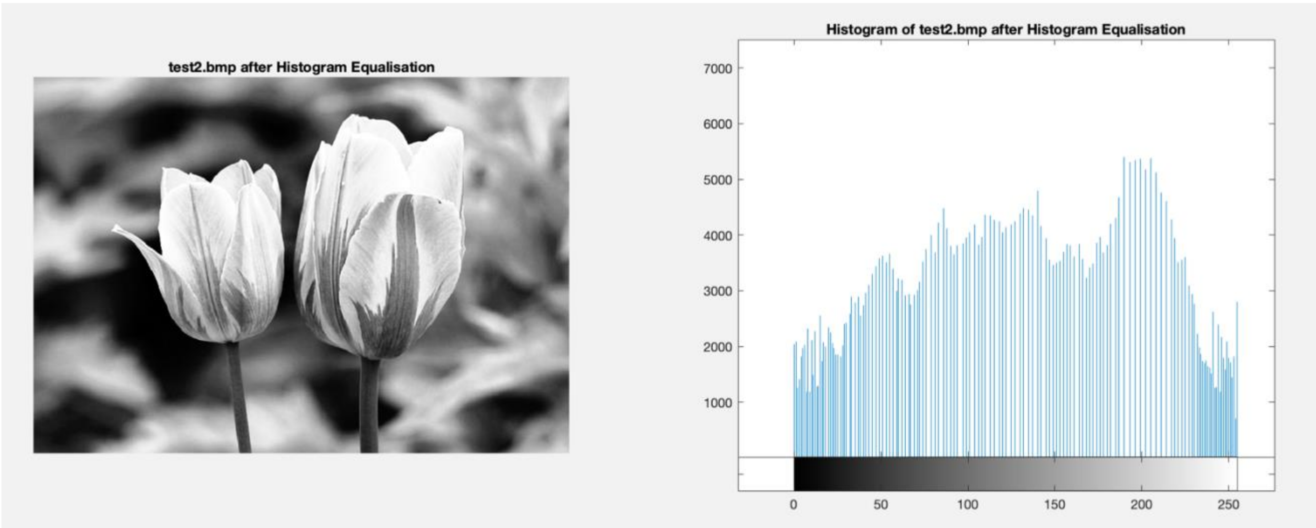

Fig. 27. Image after Histogram Equalisation of test2.bmp and corresponding Histogram

The image after histogram equalization (HE) produced very impressive results. It does a good job of boosting the contrast of the image by stretching out its intensity range, which we can observe happening in the histogram in Fig. 27. Moreover, the HE solution managed to heavily minimise clipping at 0 and 255, as we can see from the lack of clipped pixels at the extreme ends of the histogram in Fig. 27. By just observing the image from the screenshot, it might not be immediately visible what the details that were salvaged from the minimized clipping are. However, in other cases of images having very fine details in the extreme dark and extreme bright regions of the image, the minimized clipping could save many fine image details from being lost. Comparing the result of HE versus the best result from the transformation function (Fig. 26), I feel that the HE solution did a more elegant job because not only did it boost image contrast to output a more visually appealing image, it also did so without clipping extra pixels, thus image details were not lost in the process.