CS 474 Image Processing and Interpretation

Assignment 1 Image Fundamentals and Equalization

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Image Sampling

Theory

For an image to be digitized it must first be sampled. Sampling is determined by the sensor arrangement in the given instrument used to capture an image. The image can be described as a continuous uninterrupted function in 2 dimensional space. Let f represent a continuous image, we can then convert this function into discrete coordinate locations denoted as $f(x,y)$. The notation for referring to physical coordinates is denoted as $f(i,j)$ where i and j are integers. Thus, our continuous image is converted into a digital representation. Given an image with an arbitrary number of pixel samples we can further sub-sample the image to reduce the number of samples. Assume we have an image with 256 samples, we can sub-sample the image by a factor of 2, 4, and 8 and produce images with 128, 64, and 32 samples respectively. In order to subsample image by a factor of 2 we need to map every second pixel to a new image. Checking if a pixel at a given location is divisible by 2 will determine if that pixel is mapped to a new image. The above can also be used to determine pixel mapping for 4 and 8 sub-samples. After our image has been sub-sampled, we will resize it back to 256x256. This can be achieved by using a window of size 2, 4, and 8. We take each pixel of our subsampled image and map it to our window sizes.

Results

Taking our original image of size 256x256 shown in Fig. 1. We reduce the number of samples to 128, 64, and 32 and resize to 256x256. Reducing samples to 128 produces slightly more pixelated image however clarity and features are still clearly visible as seen in Fig. 2. Further sampling by a factor of 4 in Fig. 2, produces a 64x64 image which gives us an image highly pixelated. With this subsample some details are lost but the overall form can still be made out. Finally subsampling the image by a factor of 8 in figure 3, gives an image that has lost nearly all detail and only a basic structure can be derived.

Fig 1. Original image with 256 samples.

Fig 2. Image sampled by a factor of 2, producing a slightly more pixelated image.

Fig 3. Image sampled by a factor of 4. Some details are lost, but overall form is still visible.

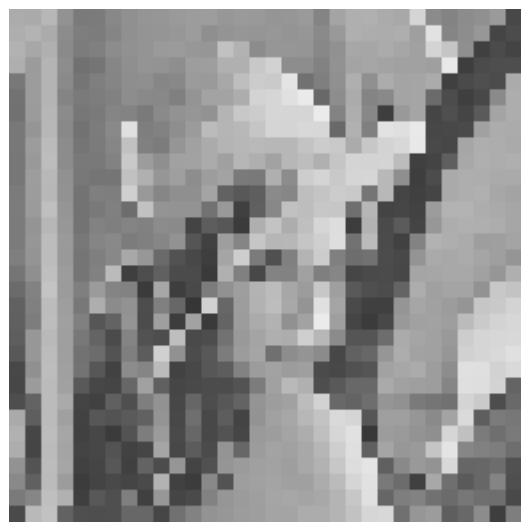

Fig 4. Image after sampling by a factor of 8. Nearly all detail is lost and only a basic structure is visible.

Performing sampling on a different image in Fig. 5-8 producing similar results where image detail and structure is degraded as sampling factor increases.

Fig 5. Original image with 256 samples.

Fig 6. Image sampled by a factor of 2, producing a slightly more pixelated image.

Fig 7. Image sampled by a factor of 4. Some details are lost, but overall form is still visible.

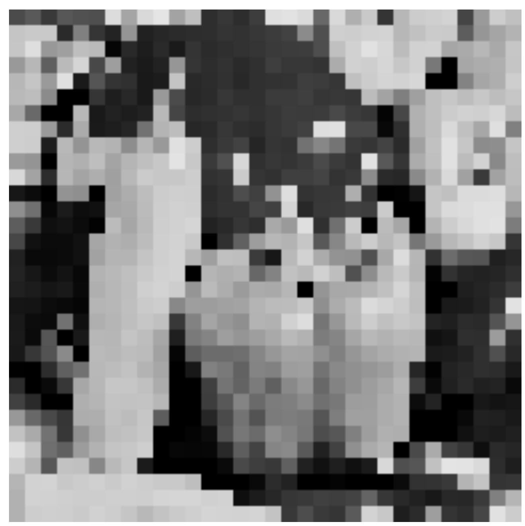

Fig 8. Image after sampling by a factor of 8. Nearly all detail is lost and only a basic structure is visible.

Image Quantization

Theory

The next step in digitizing images after sampling is image quantization. After sampling the image function into discrete spatial location, the intensity value at those locations still spans a continuous range. These values must be quantized into discrete quantities. This process of quantization reduces data needed to store an image. By converting intensity values to discrete quantities fewer bits will be needed to represent the image. The accuracy achieved during quantization is highly dependent on random variations of pixel values referred to as noise. When referring to value of an image at any location *(x,y)* is denoted as *f(x,y)*. When *(x,y)* are integers from Z^2 (cartesian product) and *f* assigns intensity values to discrete coordinates then the function process of *f(x,y)* is quantization. In the process of image digitization and hardware consideration the number of intensity levels *L* must be a power of 2 such that $L=2^k$ where k is an integer, the levels are equally spaces and are integers in the range of *[0,L-1]*. Given an image with 255 gray levels *L*=256 we will reduce the levels to 128, 32, 8, and 2. This reduction can be given as *f(x,y)=255/L*, this will reduce gray levels by a factor of *L*. For visualization we will subsample the gray levels back to 255. Which is given by *Q(x,y)=(f(x,y)//255/L)*255/L*.

Results

Reducing our original image in Fig. 9 to 128 gray levels produces an image with no noticeable difference in Fig. 10. A further reduction to 32 gray levels in Fig. 11 will produce an image with very subtle differences. I believe there are no noticeable differences with these gray levels because having 128 or 32 gray levels are still enough to provide a smooth transition of values across rounded objects in our image. Changes become very noticeable when we reduce the levels to 8 in Fig. 12. With only 8 gray levels there is not values that can be used to represent value transitions across surfaces. When reducing to 2 levels the image only has 2 values to represent values at any coordinate. This produces an image seen in Fig. 12 where the image is only represented has either a dark value or light gray level. Figures 16 -19 are quantization applied to a separate image producing similar results.

Fig 9. Original image with 255 gray levels.

Fig 10. Image reduced to 128 gray levels. No real changes are visible in this image.

Fig 11. Image reduced to 32 gray levels. Only very subtle difference can be seen.

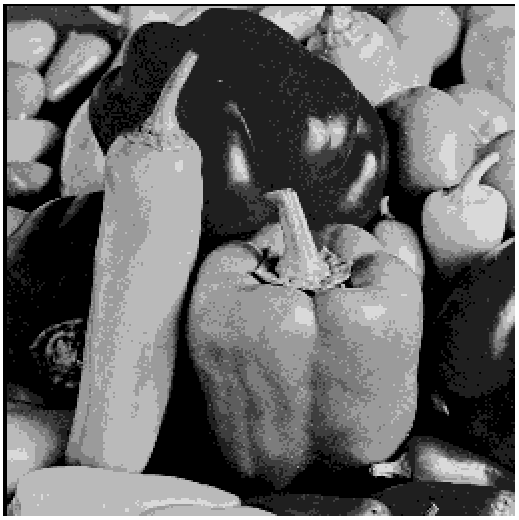

Fig 12. Image reduced to 8 gray levels. Noticeable changes can be seen since there are only 8 values to represent transitions.

Fig 13. Image with only 2 gray levels. This image only has 2 values to represent locations, gives a gray and black image.

Fig 14. Original image with 255 gray levels.

Fig 15. Image reduced to 128 gray levels. No real changes are visible in this image.

Fig 16. Image reduced to 32 gray levels. Only very subtle difference can be seen.

Fig 17. Image reduced to 8 gray levels. Noticeable changes can be seen since there are only 8 values to represent transitions.

Fig 18. Image with only 2 gray levels. This image only has 2 values to represent locations, gives a gray and black image.

Histogram Equalization

Theory

Histogram equalization is a fast to compute process and is suitable for many hardware setups. Histogram equalization is the process of taking values of an image that are biased toward being light or dark and redistributing them in a more uniform fashion. This process will produce pixel intensities that are more uniform distribution giving an image that has detailed gray level distribution, high dynamic range, and contrast enhancement. Given a gray scale image, each pixel has an intensity value in the range of 0 to 255. A histogram displays the frequency of each pixel intensity value that the image contains. This is the first step in the equalization process, keeping count of every pixel intensity. Once we have obtained the histogram, we must normalize it, so the cumulative sum of the values ranges from 0 to 1. After normalization we use the cumulative sum of the histogram values to produce a cumulative distribution function that represents the probability of a pixel intensity occurring in the image. Finally, we can map new intensity values given by *cdf*255* and redistribute intensities and improve contrast and clarity.

Results

Given an input image Fig. 19 we first calculate its histogram in Fig. 20. Looking at the histogram, pixel intensities are concentrated toward the brighter side. This corresponds with the original image which has high contrast making it difficult to make out fine details. Once we equalize the histogram Fig. 22, we can see the values be redistributed in a more uniform fashion with some values being shifted toward darker values. Applying the equalization to our image Fig. 21, the contrast has been improved and has much more gray level detail. With the improved gray levels and contrast we can see much more detail in the image, notably seen in the clouds and mountain face. In Fig. 23 this technique is applied to a separate image. This image has a histogram Fig. 24 with a high number of both dark and light values. Since we already have a good distribution of these values the equalization process produces a new histogram Fig. 26 with slightly better distribution. The equalized image Fig. 25 has slightly better contrast, however details have not improved much compared to the original image.

Fig 19. Input image with high contrast. Fine details are hard to see.

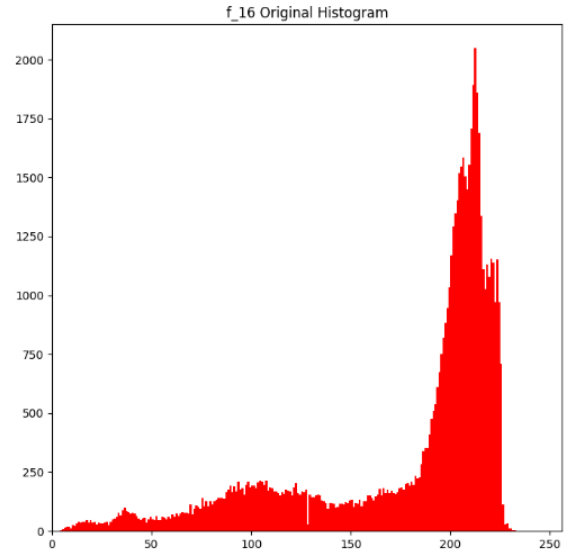

Fig 20. Image histogram. Pixel intensities are concentrated toward high values.

Fig 21. Image after equalization. Gray level detail is greatly improved, and more details can be seen.

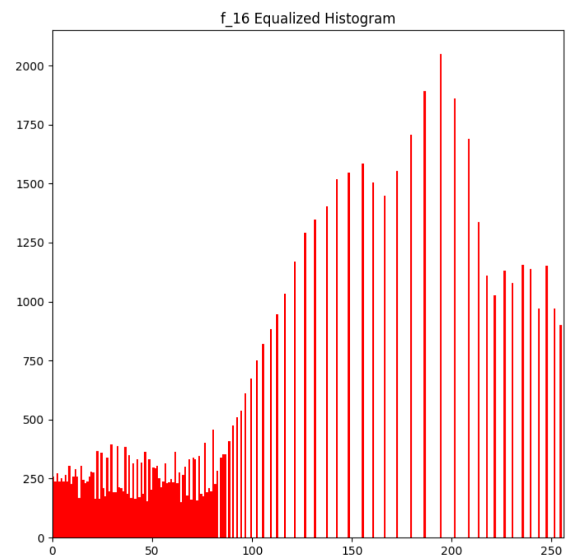

Fig 22. Equalized histogram. Intensities are redistributed producing a uniform image.

Fig 23. Input image that already has good distribution of intensities.

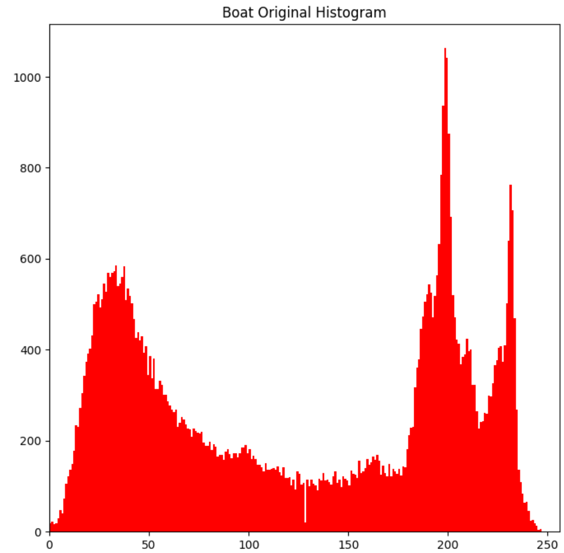

Fig 24. Image histogram with intensities distributed both on darker and lighter values.

Fig 25. Image after equalization. Gray level and contrast detail has been slightly improved.

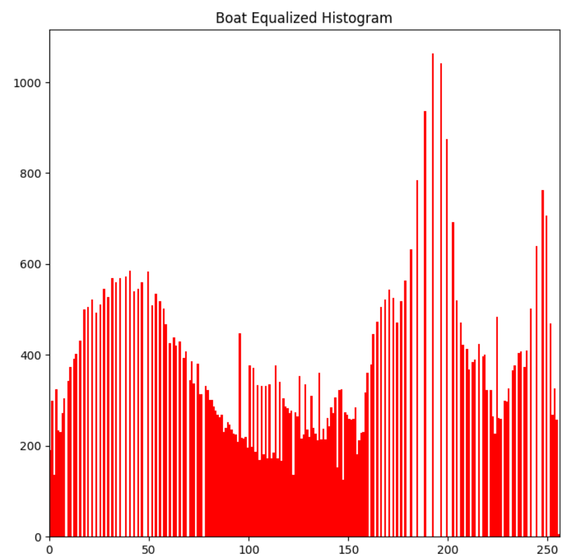

Fig 26. Equalized histogram. Pixel intensities have been redistributed in a more uniform matter.