Techniques and Algorithm Design for the Detection of PSNR in Digital Images

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Abstract
The problem of detection and removal of noise in digital images is Vast. Many techniques have been used for removal of noise from the given set of images. In this paper, we present algorithm that can be used for removal of various type of noise for the given test images. Various classifiers have been proposed. We proposed PSNR with varying threshold as the algorithm for the removal of noise and classification of the images. The algorithm gives us a clear boundary or specifically a hyper plane that separate noisy and non-noisy images.

Keywords
Digital Image, Classifier, PSNR,Resolution etc.

I. Introduction
Section II introduced about digital image. Section III describes Image Noise and methodology used for noise removal. Section IV shows PSNR method. Section V shows Conclusion. Section VI is references.

II. Introduction
A digital image is a discrete two-dimensional function f(x,y) which has been quantized over its domain and range . Without loss of generality, it will be assumed that the image is rectangular, consisting of x rows and y columns.[1] The resolution of such an image is written as x*y. By convention, f(0 0) is taken to be the top left corner of the image, and .w)f(x-1,y-1) the bottom right corner. This is summarized in Figure 1. Each distinct coordinate in an image is called a pixel, which is short for picture element. The nature of the output of f(x,y) for each pixel is

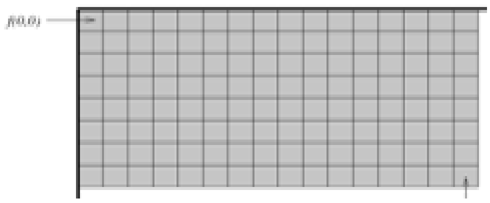


Figure 1: General description of image

dependent on the type of image. Most images are the result of measuring a specific physical phenomenon, such as light, heat, distance, or energy. The measurement could take any numerical form. A grayscale image measures light intensity only. Each pixel is a scalar proportional to the brightness. The minimum brightness is called black, and the maximum brightness is called white. A typical example is given in Figure 2. A color image [2]measures the intensity and chrominance of light. Each color pixel is a vector of color components. Common color spaces are RGB (red, green and blue), HSV (hue, saturation, value), and CMYK (cyan, magenta, yellow, black), which is used in the printing industry. Pixels in a range image measure the depth of distance to an object in the scene. Range data is commonly used in machine vision applications.

Figure 2: A typical greyscale image of resolution 512*512.

For storage purposes, pixel values need to be quantized. The brightness in grayscale images is usually quantized to levels, so f(x,y) belongs to {0 1 …...z-1} .If z has the form 2L the image is referred to as having L ¡bits per pixel. Many common grayscale images use 8 bits per pixel giving 256 distinct grey levels. This is a rough bound on the number of different intensities the human visual system is able to discern. For the same reasons, each component in a colour pixel is usually stored using 8 bit.

Medical scans often use 12-16 bits per pixel, because their accuracy could be critically important. Those images to be processed predominantly by[6] machine may often use higher values to avoid loss of accuracy throughout processing. Images not encoding visible light intensity, such as range data, may also require a larger value of z to store sufficient distance information.

There are many other types of pixels. Some measure bands of the electromagnetic spectrum such as infra-red or radio, or[5] heat, in the case of thermal images. Volume images are actually three dimensional images, with each pixel being called a voxel. In some cases, volume images may be treated as adjacent two-dimensional image slices. Although this thesis deals with grayscale images, it is often straightforward to extend the methods to function with different types of images.

III. Image Noise
Any real world sensor is affected by a certain degree of noise, whether it is thermal, electrical or otherwise. This noise will corrupt the true measurement of the signal, such that any resulting data[5] is a combination of signal and noise. Additive noise, probably the most common type, can be expressed as:

I(t) = S(t) + N(t) Equation (1) where I(t) is the resulting data measured at time t, S(t) is the original signal measured, and N(t) is the noise introduced by the sampling process, environment and other sources of interference.

A. Removal Of Noise
Removing noise from an image as noise is being random errors in the image. An example is given in Figure 3. Noise is

a very common problem in data transmission. All [3] sorts of electronic components may affect data passing through them, and the results may be undesirable. Noise may take many different forms, each type of noise requiring a different method of removal.

(a)An Original Image (b) After Removing Noise

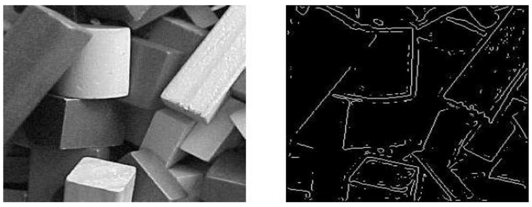
Figure 3 Removing noises from an image

Removing motion blur from an image. An example is given in Figure 3. Note that in the de blurred image (b) it is easy to read the number plate, and to see the spokes on the wheels of the car, as well as other details not at all clear in the original image (a). Motion blur may occur when the shutter speed of the camera is too long for the speed[5] of the object. In photographs of fast moving objects: athletes, vehicles for example, the problem of blur may be considerable.

(a)An Original Image (b) After removing blurs

Figure 4 Image deblurring

Examples of (2) may include: Obtaining the edges of an image. This may be necessary for the measurement of objects in an image; an example [6]is shown in Figures 4. Once we have the edges we can measure their spread, and the area contained within them. We can also use edge detection algorithms as a First step in edge enhancement, as we saw above.



(a)An Original Image (b) Its edge Image
Figure 5 Finding edges in an image

Removing detail from an image for measurement or counting purposes we may [6]not be interested in all the detail in an image. For example, a machine inspected items on an assembly line; the only matters of interest may be shape, size or color. For such cases, we might want to simplify the image. Figure 6 shows an example: in image (a) is a picture of an African buffalo, and image (b) shows a blurred version in which extraneous detail (like the logs of wood in the background) has been removed. Notice that in image (b) all the fine detail is gone; what remains is the coarse structure of the image. We could for example, measure their size and shape of the animal without being distracted by unnecessary detail.

(a)An Original Image (b) Blurring to Remove

Figure 6 Blurring an image

IV. Peak Signal to Noise Ratio

The phrase Peak Signal to Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupted noise that affects the fidelity of its representation. As many signals have wide dynamic. The MSE and PSNR is defined as below formulas

$$\text{MSE}=\frac{1}{M}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(I(i,j)-K(i,j)\right)^2$$

$$\text{PSNR}=10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)=20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

Equation 2 and 3

The proposed algorithm work as follow :

A. Algorithm for the PSNR

1. For Any Image I
2. Initialize i,k
3. Define MAX
4. Define M,N
    a. For M to M-1, Select i
    b. Calculate MSE
        aa. If i<M-1
    c. Calculate PSNR

/*Display (Input Image and PSNR value)

Else

    d. Terminate

/*Display (Image too big to render)

Here, MAXI is the maximum pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. Compression systems like JPEG include optional pre-processing with filtering to avoid compression artifacts. At higher compression ratios a stronger filtering is needed that impacts the large scale image content. Here typical diffusion processes is applied before the block wise DCT compression using the peak signal to noise ratio (PSNR) as an objective quality measure. We give a simple measure of artifact reduction in terms of PSNR, and show that a considerable artifact reduction is achieved by pre-processing at the same bit rate as and with no greater error than the original compression. We did tests to see if the above Noise removal and outputs artifact reduction implies a better subjective impression of quality. The images processed with the PSNR-based algorithm had nearly the same but greater PSNR value as the original compression and lesser Gaussian noise . Subjects preferred noisy image content to the lack of small scale details, so the subjective preference of the images with reduced artifact is worse that of the original compression.

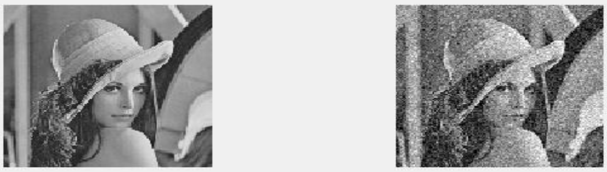


Figure 7: Gaussian Noise Value :.009

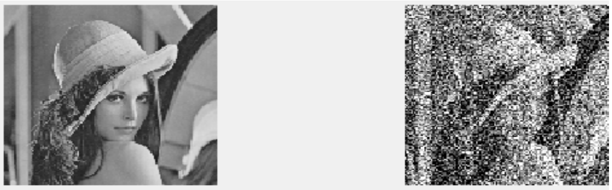


Figure 8: Gaussian Noise Value :.09

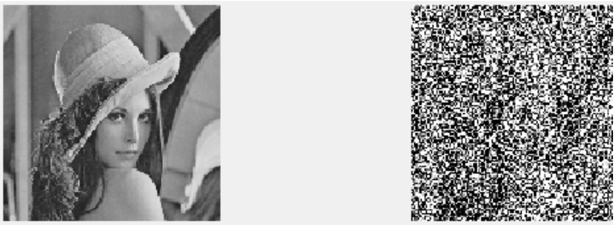


Figure 8: Gaussian Noise Value :.9

Results suggest however that non-linear diffusion is more efficient for artefact reduction than non-adaptive smoothing as given Gaussian filtering in terms of the subjective preference.

V. Conclusion

Lossy image and video compression yield typical error patterns on the decompressed images or video sequences due to the quantization error. Depending on the compression scheme and the bit rate, these can be ringing patterns around the edges, false or blurred texture, visible block-boundaries in block-partitioning schemes . These phenomena are called compression artifacts. Compression artifacts not only deteriorate

We define what we mean by Noise reduction, and use a simple way of measuring and expressing it through PSNR. To check whether Noise reduction results in images that are more preferred by human observers, subjective tests were done to rate the different methods. Results on test images suggest that the block boundaries and false textures are alleviated in the pre-processed images. The diffusion strength is controlled by PSNR measurements. The graphical view suggest that as we increase the noise or Gaussian content to the test image more prominent is the distortion and hence lesser is the value of PSNR.

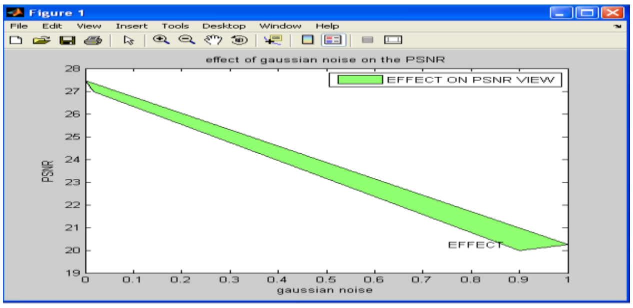


Figure 9: NOISE=X-Axis(0-1),PSNR=Y-Axis(19-28)

X-axis shows the range for Gaussian noise from 0-1 in our case and corresponding PSNR from the y-axis keep on decreasing with the increment in the noise.

from the figure 9 we can calculate any sudden impact of the noise on the PSNR and hence calculation are easy to understand.

VI. References

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