IMAGE RESTORATION

6.1 Image Degradation (Restoration) Model

(i) An image is corrupted by so many degradations which start from the stage of image acquisition itself. Images are degraded by noise, blur and distortions, or artefacts.

(ii) This process of image degradation happens in all the stages-image acquisition, image processing, image storage, and transmission. Noise is a disturbance which causes fluctuations in the pixel values. Similarly, the image capturing system itself does not capture a point as a point. Instead, it produces a blur. Thus the image formation itself introduces problems.

(iii) Image restoration is the process of retrieval of the original image from a degraded image. The idea is to obtain an image as close to the original image as possible. This is possible by removing or by minimizing the degradations.

(iv) Point spread function (PSF) or modulation transfer function (MTF) provides quantitative information about the effectiveness of the imaging system.

(v) There are many ways of restoring the image. One can attempt to construct a model and to characterize the degradations. This is called as *estimation approach*. Image restoration starts with an image degradation (or restoration) model which is shown in Fig.

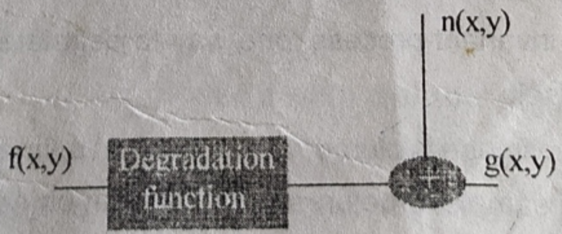


Fig.Degradation modelling

Degradation modelling

(vi) Let the original image be f(x, y). When the image is acquired by the imaging system, the degradation starts. The degradation function is denoted as h(x, y). Noise is known to affect the image and is denoted as $\eta(x, y)$. For such a linear space invariant (LSI) system, the degraded image is given as

REDMI NOTE 8
AI QUAD CAMERA

$$g(x,y) = f(x,y) * h(x,y) + \eta(x,y)$$

Here * is convolution operation. In LSI system, the degradation is modelled as an operator 'h'. 'h' has the following properties:

1. H is a linear operator.
2. It obeys the rules of homogeneity.
3. It is position-invariant.

By applying the Fourier transform, the equation in the frequency domain becomes

$$G(u,v) = F(u,v) \times H(u,v) + N(u,v)$$

The original image can be retrieved by rearranging the equation to get

$$F(u,v) = \frac{G(u,v)}{H(u,v)} - \frac{N(u,v)}{H(u,v)}$$

The original imaged f(x,y) can be obtained by applying an inverse Fourier transform to F(u, v). The idea of removing both noise and blur is called inverse filtering. The whole concept of image restoration revolves around estimating the degradation function h(x, y).

6.2 Estimating the Degradation Function

There are three (3) basic principle ways to estimate the degradation function for use in image restoration :

(1) Observation

(2) Experimentation

(3) Mathematical Modeling

Estimation by Image Observation

(i) Suppose that we are given a degraded image without any knowledge about the degradation function H. Based on the assumption that the image was degraded by a linear, position - invariant process, one way to estimate H is togather information from the image itself.

(ii) For example, if the image is blured, we can look at a small rectangular section of the image containing sample structures like part of an object and the background.

(iii) In order to reduce the effect of noise, we would look for an area in which the signal content is strong. The next step would be to process the subimage to arrive at a result that is as unblurred as possible. For example, we can do this by sharpening the subimage with a sharpening filter and even by processing small areas by hand.

(iv) Let the observed subimage be denoted by $g_s(x,y)$, and let the processed subimage be denoted by $f_s(x,y)$. Then, assuming that the effect of noise is negligible because

REDMI NOTE 8
AI QUAD CAMERA

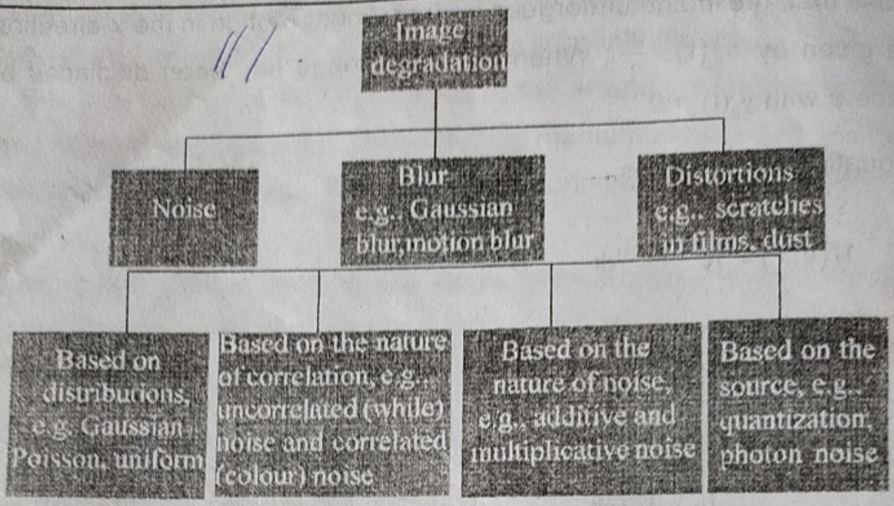


Fig. Types of degradations

6.3.1. Noise Modelling

Noise is a disturbance which causes fluctuations in the pixel values. Hence the pixel values show random variations and this cannot be avoided Hence, suitable strategies should be designed to model and manage noise. Noise can be viewed in multiple ways. Some the frequent noises that are encountered in image processing are categorized based on the criteria of distributions, correlation, nature, and source.

6.3.1.1. Noise categories based on distribution

Since noise is a fluctuation of pixel values, it is characterized as a random variable. A random variable probability distribution is an equation mat links the values of the statistical result with its probability of occurrence. Noise categorization based on probability distributions is very popular. On the basis of its distribution, noise can be classified as follows:

Gaussian distribution : The Gaussian distribution is a well known bell-shaped curve. The random noise that enters the system can be modelled as a Gaussian or normal distribution. This is mathematically denoted as $F = S \pm N_a$, where N_a is the Gaussian probability density function (PDF) and S is the noiseless image. The Gaussian noise affects both the dark and light areas of the image. A sample image and its Gaussian noise-affected counterparts are shown in Figs.(a)–(d).

REDMI NOTE 8
AI QUAD CAMERA

Gaussian probability distributive function.

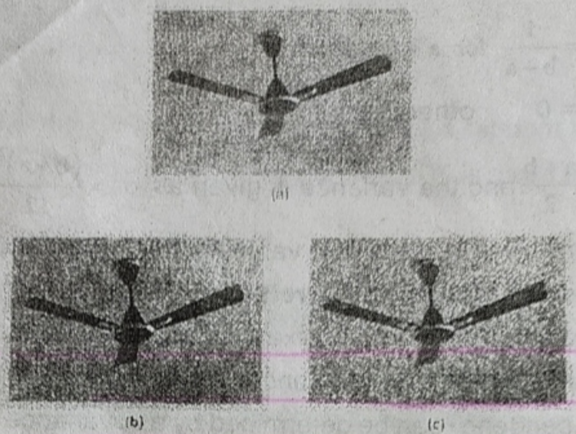


Fig. Speckle noise (a) Original image (b) Image with speckle noise of default mean = 0 and variance = 0.04(c) Image with speckle noise of variance = 0.01

Periodic Noise: This type of noise is sinusoidal at multiples of a specific frequency and is periodic. The occurrence of uniform bars over an image is a manifestation of periodic noise. An original image and an image with periodic noise are shown in Figs (a) and (b), respectively. Periodic noise mostly occurs due to electrical interferences.

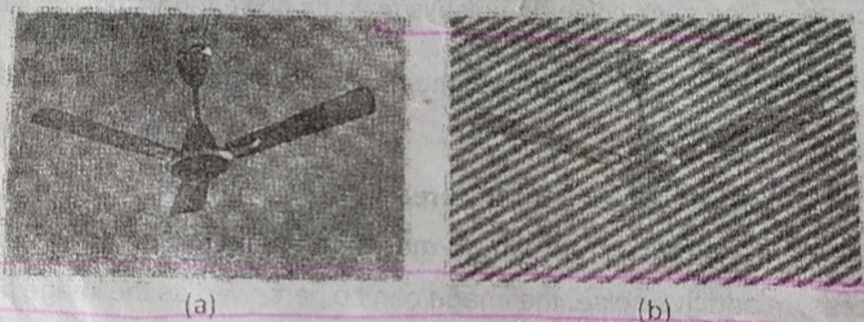


Fig. Periodic noise (a) Original image(b) Image with periodic noise

6.3.1.4. Noise Categories Based on Source

Based on this criterion, some of the frequently encountered noises in image processing are quantization noise and photon noise. Quantization noise is inherent in the quantization process. This is due to the difference between the actual and allotted values. Photon noise occurs due to the statistical nature of electromagnetic waves. In many medical images, the pixel value is the count of photons. Due to the statistical variations of nature, the generation of photons is not constant. This causes variations in photon count which can be termed as photon noise.

7.1.3. Parameters of Colour Image Processing

The essence of colour image processing can be calculated by the following 3 paramet

(a) Brightness

(b) The

(c) Saturation

Brightness: Brightness or Luminance is the power of light and is indicated by the area under the entire spectram.

Hue: The dominant wavelength (the location of the spike in the pectral density curve) is called **Hue.**

Saturation: It is measured as a percentage of the luminance in the dominant component of the spectrum.

7.2 Colour Models

(i) Colour spaces or colour models are used interchangeably in image processing.

(ii) Colour space is a mathematical, virtual model and allows representation, creation, visualization, and reproduction of colours.

(iii) Colours are represented as a tuple of numbers (mostly three numbers and as four numbers in the CMYK model). A set of colours is described as an abstract mathematical model called a **colour model** (or colour gamut).

(iv) The colour model is not associated with any mapping functions connecting its space with the external world. Hence mapping functions are introduced to map the colour model with the reference colour space. Hence, the colour model and the mapping function are together known as the **colour space**.

Facts to Know:

The reference standard is given by CIE standards such as CIEXYZ and its derivatives namely CIELUV and CIELAB. These are known as reference models. The advantages of reference standards are device independence and perceptual linearity.

There are many ways of classifying colour models. One such system of classification is as follows:

Primary systems These are colour models that are based on the trichromatic theory. Examples of primary systems include RGB and CIEXYZ. CIEXYZ is also a reference. RGB is a very popular standard due to the fact that the human visual system is very similar to the RGB model. Some of the disadvantages of the RGB model include its non-linearity (as the addition of a number makes it difficult to predict the resultant code and perceptual non-uniformity. RGB models are not intuitive and have high correlation of information among the channels.

Luminance-chrominance systems: These systems use one component for luminance and two components for chrominance part. Examples include L * U * V * and L * a * b *.

7.2.1. RGB Colour Model

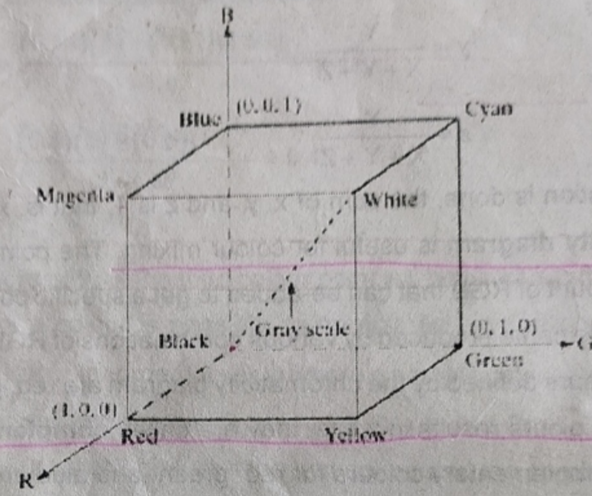
26/11

This is the most common format, where the colours are represented in a cube. Each point in the cube is represented by a colour. The origin is represented by black while the

RGB MODEL

opposite corner is represented by white. This model is used in TV, cameras, scanners, and computer monitors. The lines connecting the primaries represent the various shades of the given colour.

Some of the colour shapes are shown in Fig.



7.2.2. HSI Colour Model

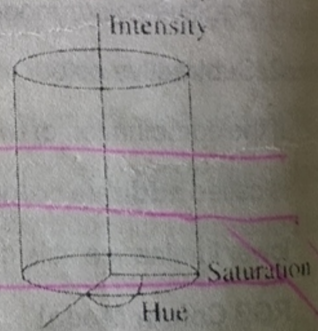
The human perception of colour closely resembly the HSI colour model. Here H represents hue, S represents saturation, and I represents intensity. The component I is the average of the R, G, and B components, and hue is expressed as an angle.

RGB can be converted to HSI using a set of formula as follows:

$$H\begin{cases}\theta \text{ if } B \le G\\ 360-\theta \text{ if } B > G\end{cases}$$

with

$$\theta = \cos^{-1}\left\{\frac{0.5\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}}\right\}$$



HSI

$$S = 1-\frac{3}{(R+G+B)}\left[\min(R,G,B)\right]$$

$$I = \frac{1}{3}(R+G+B)$$

REDMI NOTE 8
AI QUAD CAMERA

7.2.3. HSV Colour Model

The components of this model are hue, saturation, arid value. These components specify the colour. Alternatively, it can be called HSB. Here B is the brightness component. Like the RGB model, this is represented by a six-sided pyramid. The vertical axis is called brightness, the horizontal distance from the axis represents the saturation, and the angle represents the hue.

The RGB model can be converted to the HSV model using the following procedure:

1. Calculate the maximum of the RGB component. This is called k_{max}. The minimum of the RGB component is k_{min}. The range k is given as $k = k_{max} - k_{min}$.
2. The saturation can be calculated as follows:

REDMI NOTE 8
AI QUAD CAMERA

$$S = \begin{cases} \dfrac{k}{k_{max}} & \text{for } k_{max} > 0; \\ 0 & \text{otherwise} \end{cases}$$

3. The luminance is given as

$$V = k_{max} / r_{max}$$

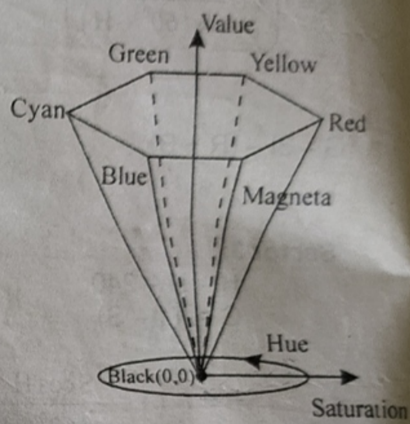
where r_{max} is the maximum component value as R, G, $B \in [0, ..., r_{max}]$

4. Normalize the components as follows:

$$R' = \frac{k_{max} - R}{k}$$

$$G' = \frac{k_{max} - G}{k}$$

$$B' = \frac{k_{max} - B}{k}$$



5. Similarly, the hue can be calculated as follows:

$$H' = \begin{cases} B' - G' & \text{if } R = k_{max} \\ R' - B' + 2 & \text{if } G = k_{max} \\ G' - R' + 4 & \text{if } B = k_{max} \end{cases}$$

The normalized hue is in the rantge 0 – 1 and is given as

$$H = \frac{1}{6} \times \begin{cases} (H' + 6) & \text{for } H' < 0 \\ H' & \text{otherwise} \end{cases}$$

For any angle, say 360°, the HSV can be calculated by multiplying the angle with value. The plot of the colour components are shown in Fig.(a) and the conversion of the RGB colour rnodel to the HSV model .is shown in Fig.(b) and (c).

REDMI NOTE 8
AI QUAD CAMERA

Example - 2. *Let the RGB values of a point be (0.4, 0.6, 0.8). Find the HSV equivalent of RGB. Also verify whether the original point can be obtained by the inverse transform from HSV to RGB.*

Soln. Given RGB values are R = 0.4, G = 0.6, and B = 0.8

$$k_{max} = \max\{R, G, B\} = \max\{0.4, 0.6, 0.8\} = 0.8$$

$$k_{min} = \min\{0.4, 0.6, 0.8\} = 0.4$$

$$k = 0.8 - 0.4 = 0.4$$

Therefore, $V = k_{max} = 0.8$

$$S = \frac{k}{k_{max}} = \frac{0.4}{0.8} = 0.5$$

$$R' = \frac{k_{max} - R}{k} = \frac{0.8 - 0.4}{0.4} = 1$$

$$G' = \frac{k_{max} - G}{k} = \frac{0.8 - 0.6}{0.4} = 0.5$$

$$B' = \frac{k_{max} - B}{k} = \frac{0.8 - 0.8}{0.4} = 0$$

REDMI NOTE 8
AI QUAD CAMERA

Finally, $H' = G' - R' + 4 = 0.5 - 1 + 4 = 3.5$

Since

$$H' > 0$$

$$H = \frac{1}{6} \times 3.5 = 0.58$$

Finally the HSV point corresponding to the given RGB point is (0.58, 0.5, 0.8). This can be converted back to RGB. Since $\lfloor H' \rfloor \lfloor 3.48 \rfloor = 3$, for case 3, the resultant (RGB) is (x, y, ν). Here $\nu = V$. Therefore V = 0.8. The remaining values of x and y can be calculated using the given formula:

$$x = (1 - S) \times V = (1 - 0.5) \times 0.8 = 0.4$$

$$y = (1 - (S \times (H - \lfloor H' \rfloor))) \times 0.8 = 0.76 \times 0.8 \overset{\Omega}{=} 0.6$$

Therefore sthe original values of RGB are exactly obtained.

7.2.5.

7.2.