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Internal Assessment Test 3 – December 2024

Sub:	Digital Image Processing				Sub Code:	21EC722	Branch:	ECE
Date:	15-12-2024	Duration:	90 min's	Max Marks: 50	Sem / Sec:	7 – A, B, C, D		OBE

	Answer any FIVE FULL Questions	MARKS	CO	RBT
1.	Briefly explain the color models. a) RGB color model. b) CMY/CMYK color model. c) HSI Color model.	[10]	CO4	L1
2.	Write a note on pseudo color image processing. Explain intensity slicing as applied to color image processing.	[10]	CO4	L1
3.	Explain the color characteristics to distinguish between various colors. Write the trichromaticinterms of X, Y and Z.	[10]	CO4	L2
4.	Explain the model of image degradation/restoration.	[10]	CO5	L2
5.	Explain all the noise probability density functions.	[10]	CO5	L2
6.	Derive an expression of the linear degradation model in presence of additive noise.	[10]	CO5	L2
7.	What are the three methods of estimating the degradation function? Explain each of them	[10]	CO5	L2
8.	Explain briefly inverse filtering and Weiner filtering in image processing.	[10]	CO5	L1

1.RGB Color model:

RGB: The RGB colour model is the most common colour model used in Digital image processing and openCV. The colour image consists of 3 channels. One channel each for one colour. Red, Green and Blue are the main colour components of this model. All other colours are produced by the proportional ratio of these three colours only. 0 represents the black and as the value increases the colour intensity increases.

Properties:

- This is an additive colour model. The colours are added to the black.
- 3 main channels: Red, Green and Blue.
- Used in DIP, openCV and online logos.

CMY Color model:

- **Cyan, magenta and yellow** are the secondary colors of light and the primary colors of pigments. This means, if white light is shined on a surface coated with cyan pigment, no red light is reflected from it. Cyan subtracts red light from white light. Unlike the RGB color model, CMY is **subtractive**, meaning higher values are associated with darker colors rather than lighter ones.
-
- Devices that deploy pigments to color paper or other surfaces use the CMY color model, e.g. printers and copiers. The conversion from RGB to CKY is a simple operation, as is illustrated in the Python program below. It is important that all color values be normalized to [0, 1] before converting.
- **HSI Color model:**
- The HSI color space is a very important and appealing color model for applications in image processing. The HSI variety model addresses each tone with three parts: intensity (I), saturation (H), and hue The HIS color space's color representation is depicted in the figure below. The Tone part depicts the actual variety as a point between [0,360] degrees. Zero degrees are red, 120 are green, and 240 are blue. 60 degrees is yellow, 300 degrees is maroon. The amount of white color in the color is indicated by the saturation component. The scope of the S part is [0,1].
- The Force range is somewhere in the range of [0,1] and 0 methods dark, 1 method white. Hue is more important as saturation approaches 1 and less important as intensity approaches 0 or 1, as shown in the previous figure. Power additionally restricts the immersion values. To equation that

believers from RGB to HSI or back is more muddled than with other variety models, consequently we won't expand on the itemized particulars engaged with this interaction.

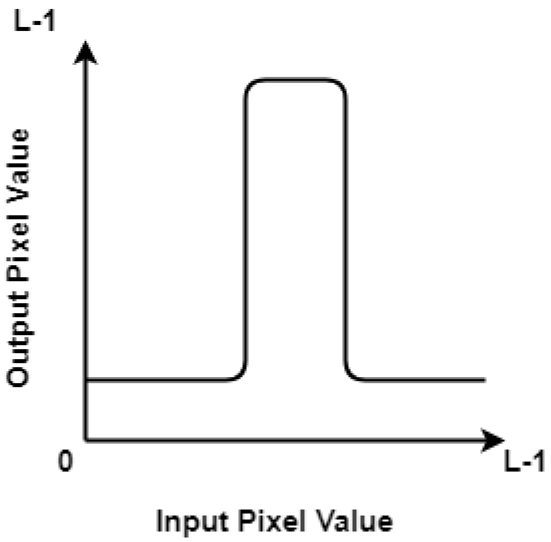
2.Intensity-level Slicing

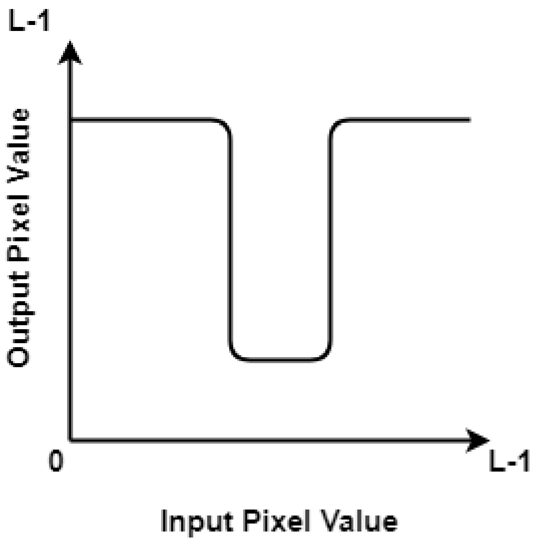
Intensity level slicing means highlighting a specific range of intensities in an image . In other words, we segment certain gray level regions from the rest of the image.

Suppose in an image, your region of interest always take value between say 80 to 150. So, intensity level slicing highlights this range and now instead of looking at the whole image, one can now focus on the highlighted region of interest.

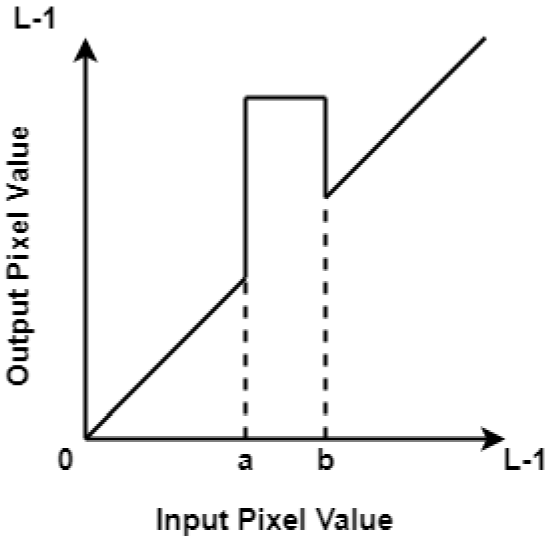
Since, one can think of it as piecewise linear transformation function so this can be implemented in several ways. Here, we will discuss the two basic type of slicing that is more often used.

- In the first type, we display the desired range of intensities in white and suppress all other intensities to black or vice versa. This results in a binary image. The transformation function for both the cases is shown below.





- In the second type, we brighten or darken the desired range of intensities(a to b as shown below) and leave other intensities unchanged or vice versa. The transformation function for both the cases, first where the desired range is changed and second where it is unchanged, is shown below.



Let’s see how to do intensity level slicing using OpenCV-Python. Below code is for type 1 as discussed above

3. Chromaticity Coordinates • Tristimulus values X, Y, Z specify a color’s: – Lightness - light or dark – Hue - red, orange, yellow, green, blue, purple – Saturation - pink-red; pastel-fluorescent; baby blue□deep blue • The chromaticity specifies the hue and saturation, but not the lightness. x = X X + Y + Z y = Y X + Y + Z z = Z X + Y + Z

Image restoration is the process of recovering an image that has been degraded by some knowledge of degradation function ***H*** and the additive noise term . Thus in restoration, degradation is modelled and its inverse process is applied to recover the original image.

4.

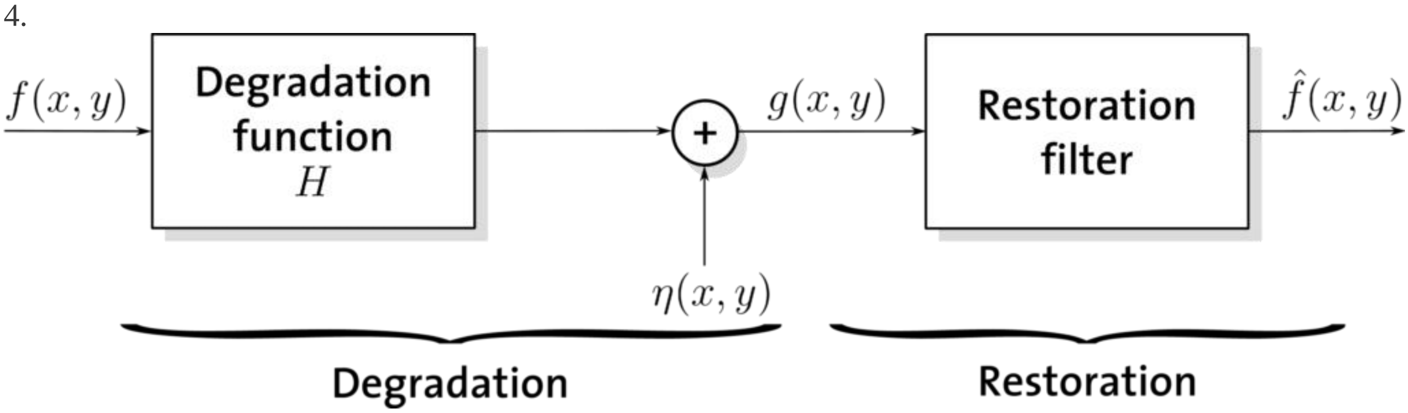


Fig: Image Restoration and Image Degradation Model

Objective of image restoration:

The objective of image restoration is to obtain an estimate of the original image . Here, by some knowledge of ***H*** and , we find the appropriate restoration filters, so that output image is as close as original image as possible since it is practically not possible (or very difficult) to completely (or exactly) restore the original image.

Terminology:

- = degraded image
- = input or original image

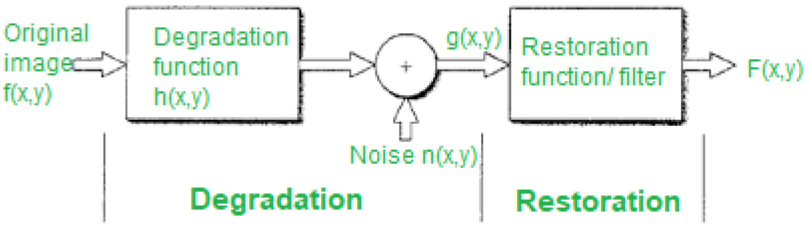
- = recovered or restored image
- = additive noise

The principal source of noise in digital images arises during image acquisition and transmission. The performance of imaging sensors is affected by a variety of environmental and mechanical factors of the instrument, resulting in the addition of undesirable noise in the image. Images are also corrupted during the transmission process due to non-ideal channel characteristics.

Generally, a mathematical model of image degradation and its restoration is used for processing. The figure below shows the presence of a degradation function *h(x,y)* and an external noise *n(x,y)* component coming into the original image signal *f(x,y)* thereby producing a final degraded image *g(x,y)*. This part composes the degradation model. Mathematically we can write the following :

Where * indicates convolution in the spatial domain.

The goal of the restoration function or the restoration filter is to obtain a close replica *F(x,y)* of the original image.



The external noise is probabilistic in nature and there are several noise models used frequently in the field of digital image processing. We have several probability density functions of the noise.

5. Noise Models
Gaussian Noise:
Because of its mathematical simplicity, the Gaussian noise model is often used in practice and even in situations where they are marginally applicable at best. Here, m is the mean and σ^2 is the variance.
Gaussian noise arises in an image due to factors such as electronic circuit noise and sensor noise due to poor illumination or high temperature.

Rayleigh Noise

Here mean m and variance σ^2 are the following:

Rayleigh noise is usually used to characterize noise phenomena in range imaging.

Erlang (or gamma) Noise

Here ! indicates factorial. The mean and variance are given below.

Gamma noise density finds application in laser imaging.

Exponential Noise

Here a > 0. The mean and variance of this noise pdf are:

This density function is a special case of b = 1.

Exponential noise is also commonly present in cases of laser imaging.

Uniform Noise

The mean and variance are given below.

Uniform noise is not practically present but is often used in numerical simulations to analyze systems.

Impulse Noise

If b > a, intensity b will appear as a light dot in the image. Conversely, level a will appear like a black dot in the image. Hence, this presence of white and black dots in the image resembles to salt-and-pepper granules, hence also called salt-and-pepper noise. When either P_a or P_b is zero, it is called unipolar noise. The origin of impulse noise is quick transients such as faulty switching in cameras or other such cases.

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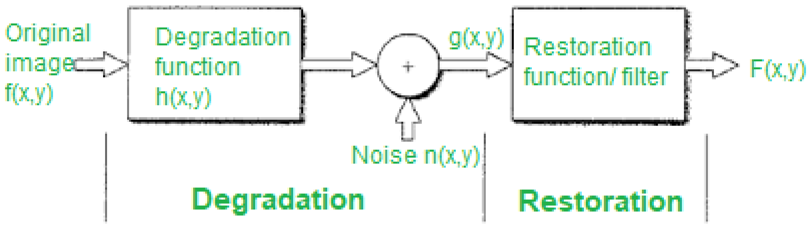

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7. Three methods of Image Restoration:
The three methods for estimating a degradation function are observation, experimentation, and mathematical modeling:

- **Observation**: In this method, you use information from the image itself to estimate the degradation function. For example, if the image is blurred, you can select a small rectangular section of the image that contains both the object and the background. You can then try to manually unblur the sub-image to generate the restored version.
- **Experimentation**: This method involves experimentally replicating the degradation.
- **Mathematical modeling**: This method involves deriving models from basic principles to describe the effects of physical processes or environmental conditions on image degradation. For example, you can develop models to characterize the degradation caused by uniform linear motion or atmospheric turbulence.

8. The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known lowpass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)},$$

where $S_{xx}(f_1, f_2), S_{\eta\eta}(f_1, f_2)$ are respectively power spectra of the original image and the additive noise, and $H(f_1, f_2)$ is the blurring filter. It is easy to see that the Wiener filter has two separate part, an inverse filtering part and a noise smoothing part. It not only performs the deconvolution by inverse filtering (highpass filtering) but also removes the noise with a compression operation (lowpass filtering).

Implementation

To implement the Wiener filter in practice we have to estimate the power spectra of the original image and the additive noise. For white additive noise the power spectrum is equal to the variance of the noise. To estimate the power spectrum of the original image many methods can be used. A direct estimate is the periodogram estimate of the power spectrum computed from the observation:

$$S_{yy}^{per} = \frac{1}{N^2}[Y(k,l)Y(k,l)^*]$$

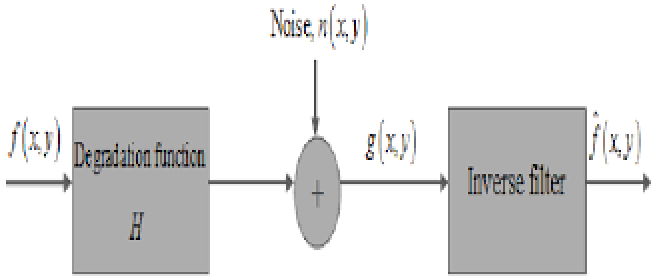
where **Y(k,l)** is the DFT of the observation. The advantage of the estimate is that it can be implemented very easily without worrying about the singularity of the inverse filtering. Another estimate which leads to a cascade implementation of the inverse filtering and the noise smoothing is

$$S_{xx} = \frac{S_{yy} - S_{\eta\eta}}{|H|^2},$$

which is a straightforward result of the fact: $S_{yy} = S_{\eta\eta} + S_{xx}|H|^2$. The power spectrum S_{yy} can be estimated directly from the observation using the periodogram estimate. This estimate results in a cascade implementation of inverse filtering and noise smoothing:

$$W = \frac{1}{H}\frac{S_{yy}^{per} - S_{\eta\eta}}{S_{yy}^{per}}.$$

The disadvantage of this implementation is that when the inverse filter is singular, we have to use the generalized inverse filtering. People also suggest the power spectrum of the original image can be estimated based on a model such as the $1/f^{\alpha}$ model.



Inverse filtering is a technique used in signal processing and image processing to recover an original signal or image from a degraded or distorted version of it. It's based on the idea of reversing the effects of a known filter or degradation process. Here are some details about inverse filtering and its applications:

1. *Basic Concept*: Inverse filtering involves the use of a mathematical operation to reverse the effects of a previously applied filter. It is particularly useful when you have prior knowledge of the filter that was applied to a signal or image.

2. *Applications*:

a. *Image Restoration*: Inverse filtering is commonly used in image processing to restore images that have been degraded by blurring, for example, due to a defocused camera or motion blur. By applying the inverse of the blurring filter, one can attempt to recover the original sharp image.

b. *Signal Deconvolution*: In the realm of signal processing, inverse filtering is used to deconvolve signals. This can help recover the original signal from a distorted or noisy version. For example, in communication systems, it can be used to mitigate channel-induced distortion.

c. *Astronomy*: In astronomy, inverse filtering is used to enhance the quality of astronomical images by compensating for atmospheric distortions, telescope imperfections, or other forms of degradation.

d. *Medical Imaging*: Inverse filtering can be applied in medical imaging to improve the quality of MRI or CT scan images by correcting for motion artifacts or other sources of degradation.

e. *Audio Processing*: In audio processing, inverse filtering can be used to reduce the impact of room reverberation or to remove the effects of a known acoustic filter, improving speech or audio quality.

f. *Seismic Imaging*: In the field of geophysics, inverse filtering is applied to seismic data to correct for the effects of the subsurface, enabling a clearer interpretation of subsurface structures.

3. *Challenges*:

Inverse filtering is a powerful technique, but it comes with some challenges:

a. *Ill-Posed Problem*: Inverse filtering can be ill-posed, meaning it may not have a unique or stable solution. Noise in the data or inaccuracies in the assumed filter can lead to unstable results.