

Digital Image Processing

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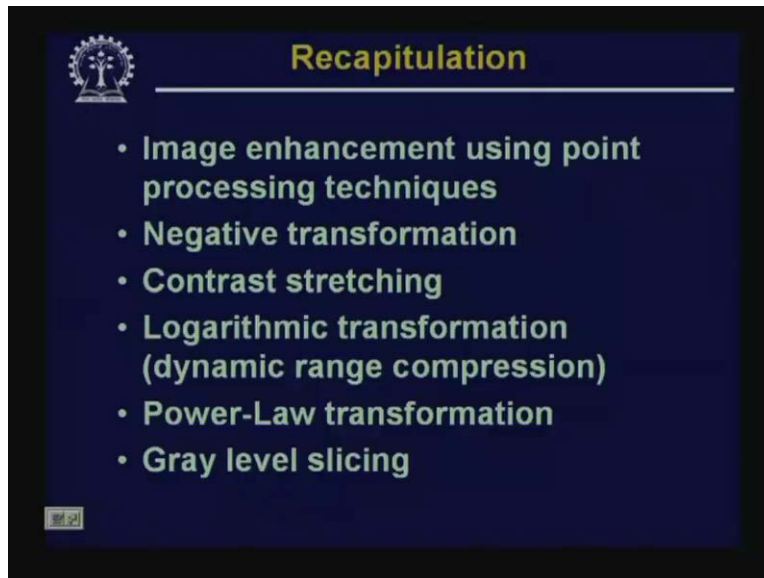
Indian Institute of Technology, Kharagpur

Lecture - 18

Image Enhancement (Point Processing - II)

Hello, welcome to the video lecture series on digital image processing. In our last class, we have discussed about the various point processing techniques.

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So, we have talked about the image enhancement using point processing and under that we have talked about the various point processing techniques like negative image transformation and in case of negative image transformation, we have seen that the processed image that we get is a negative version of the input original image and such processed images are useful in case we have very few pixels in the original image where the information content is mostly in the white pixels or gray pixels which are embedded into large regions of dark pixels

So, in such cases, if we take the negative of the image; in that case, the **processed imaging** processed image, the information content becomes much more convenient to visualize. The other kind of point processing techniques that we have discussed is the contrast stretching operation. In case of contrast stretching operation, we have seen that this kind of contrast stretching operation is useful where the original image is very dark and we have said that such dark images, we can have when the scene illumination was very poor or we can also have a very dark image

where the dynamic range of the sensor is very small so that it cannot record all the intensity values present in the scene or the dark images can also be obtained if while image acquisition, the aperture setting of the camera lens is not proper.

So, for these different kinds of cases, we can have a dark image and contrast stretching is a very very useful technique to enhance the contrast of such dark images. The other kind of transformation that we have used for image enhancement is a logarithmic transformation and there we have said that logarithmic transformation basically compresses the dynamic range of the input image and these kind of transformation, we have said that it is very very useful when an image which is to be displayed on a display device but the dynamic range of the input image is very large which the display device cannot handle. So, for such cases, you go for the logarithmic transformation which compresses the dynamic range of the input image so that it can be reproduced faithfully on the display.

Then we have also talked about the other kind of image enhancement techniques power-law transformation and we have said that this power-law transformation is very very useful for image display devices, for printing devices as well as for image acquisition devices because by nature, all these devices provide a power-law transformation of the image that is to be produced; whether it is on the display or it is on the printer or the image which is to be captured.

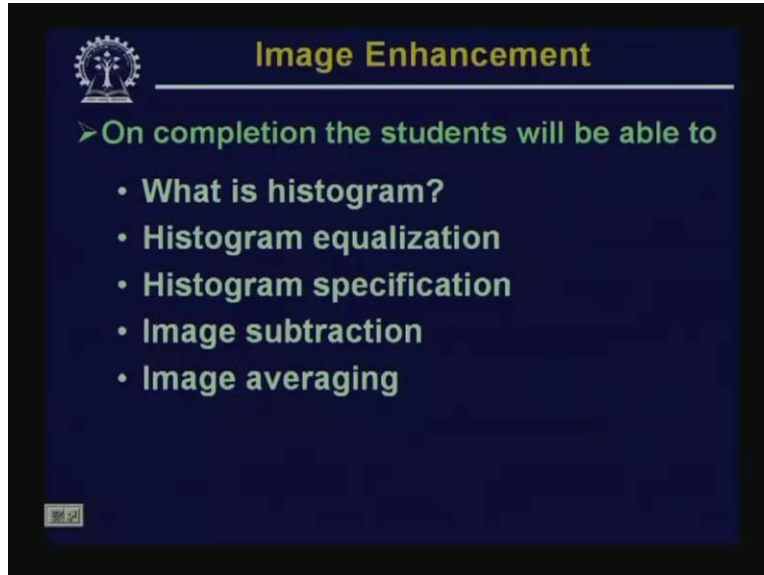
So, because the devices themselves transform the image using the power-law transformation, then if we do not take any action before providing the image to those devices, then the images which will be produced will be distorted in nature. So, the purpose of this power-law transformation is you apply a power-law transformation to the input image in such a way that it compensates the power-law transformation which is applied by the device.

So in effect, what we get is an output image; whether it is on the display or on the printer, will be a faithful reproduction of the input image. The other kind of image enhancement techniques that we have discussed about is the gray level slicing operation and we have said that these gray level slicing operations are useful for applications or the application demands or the application wants the enhanced values of certain gray levels.

So, there again, we have seen **2 different types of** 2 different types of transformation functions. In one case of transformation function, the transformation enhances all the intensity values within a given range and the intensity values outside that given range is suppressed or made to 0. The other kind of gray level slicing transformation that we have said is there within the given range, the intensity values are enhanced. But outside that particular range, the intensity values remain untouched. That is whatever is the intensity value is the in the original image, the same intensity values are reproduced in the processed image or as within the given range, the intensity values are enhanced.

So, these kinds of applications, these kinds of transformation is very very useful for applications where the application wants that intensity values within a certain range should be highlighted. Now, all these different point processing techniques that we have discussed till now, they do not consider the overall appearance of the image. They simply provide the transformation on a particular intensity value and accordingly produce the output intensity value.

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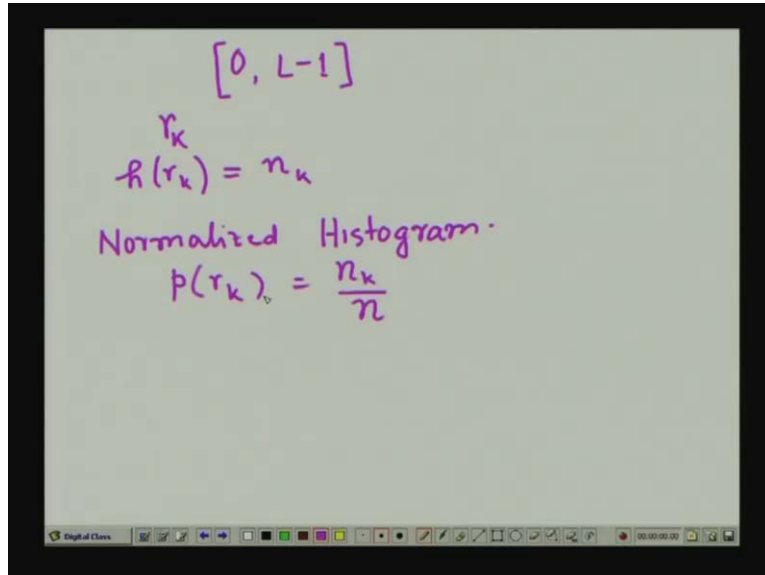
Now, in today's discussion, we will talk about another approach where the transformation techniques also take care of the global appearance of the image. So, histogram is such a measure which provides a global description of the appearance of an image. So today, what we are going to discuss, the enhancement techniques that we going to discuss; few of them are based on histogram based processing.

So, in today's discussion, we will talk about initially what is an histogram, then we will talk about 2 histogram based techniques, one of them is called histogram equalization and the other one is called histogram specification or sometimes it is also called histogram matching or histogram modification. Then apart from this histogram based techniques, we will also talk about 2 more image enhancement techniques.

You remember from our previous discussion that when we have said that a transformation function T is applied on the original image F to give us the processed image G and there we have said that this transformation function T transforms an intensity in the input image to a intensity value in the original image and there we have mentioned that it is not necessary that the transformation function T will work on a single image, the transformation function T can also work on multiple images, more than one images.

So, we will discuss 2 such approaches. One approach is image enhancement using image subtraction operation and the other approach is image enhancement using image averaging operation. So, first let us start discussion on histogram processing and before that let us see that what we mean by the histogram of an image.

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The image shows a whiteboard with handwritten mathematical definitions for a histogram. At the top, the range of intensity levels is given as $[0, L-1]$. Below that, the histogram function is defined as $h(r_k) = n_k$. The text "Normalized Histogram" is written, followed by the normalized histogram function $p(r_k) = \frac{n_k}{n}$. The whiteboard also shows a standard software toolbar at the bottom.

So, to define the histogram of an image we consider that an image is having gray level intensities in the range 0 to L minus 1. So, we will consider that the digital images that we are talking about, it will have L number of discrete intensity levels and we will represent those intensity levels in the range 0 to capital L minus 1.

And, we say that a variables r_k represents the k'th intensity level. Now, a histogram is represented by $h(r_k)$ which is equal to n_k where n_k is the number of pixels in the image having intensity level $h(r_k)$. So, once we get the number of pixels having an intensity value h having intensity value r_k and if we plot these number of pixel values, the number of pixels having different intensity values against the intensity value of that of those pixels; then the plot that we get is known as a histogram.

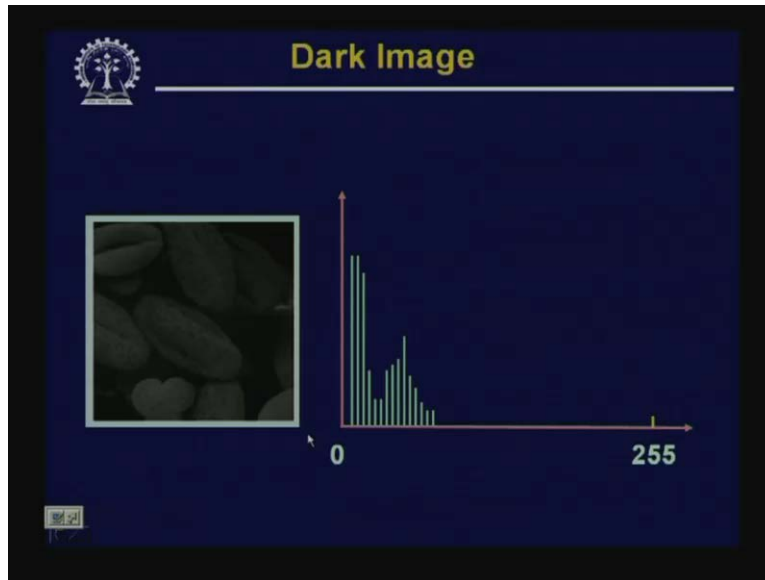
So, in this particular case, we will find that because we are considering the discrete images; so this function the histogram $h(r_k)$ will also be discrete. So here, r_k is a discrete intensity level, n_k is the number of pixels having intensity level r_k and $h(r_k)$ which is same as n_k also assumes discrete values. In many cases, we talk about what is called a normalized histogram.

So instead of taking a simple histogram as just defined, we sometimes take a normalized histogram. So, a normalized histogram is very easily derived from this original histograms or the normalized histogram is represented as $p(r_k)$ is equal to n_k by n .

So, as before this n_k is the number of pixels having intensity value r_k and n is the total number of pixels in the digital image. So, find that from this expression that $p(r_k)$ equal to n_k by n , this $p(r_k)$ actually tells you that what is the probability of occurrence of a pixel having intensity value equal to r_k and such type of histograms give as we said; information, a global description of the appearance of an image.

So now, let us see that what are the different types of images that we can usually get and what are the corresponding histograms.

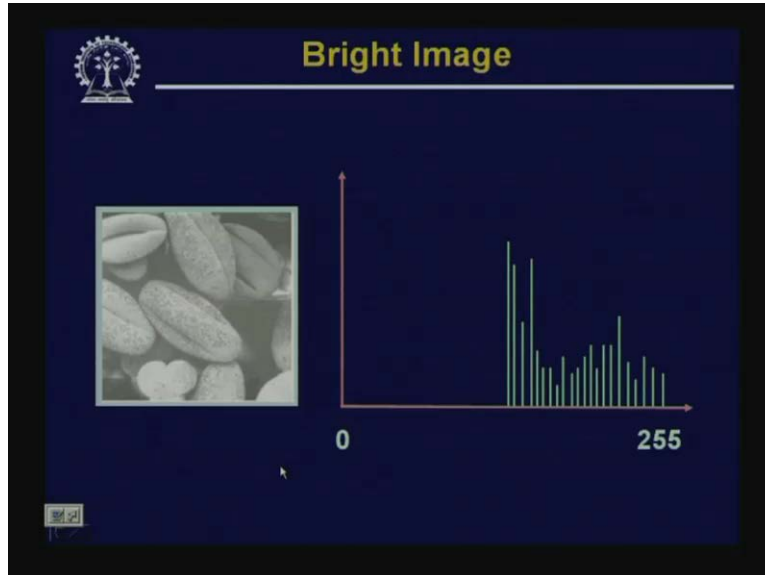
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So, here we find that the first image as you see that it is a very very dark image. It is very difficult to find out what is the content of this particular image and if we plot the histogram of this particular image, then the histogram is plotted on the right hand side. You find that this plot says that most of the pixels of this particular image have intensity values which are near to 0.

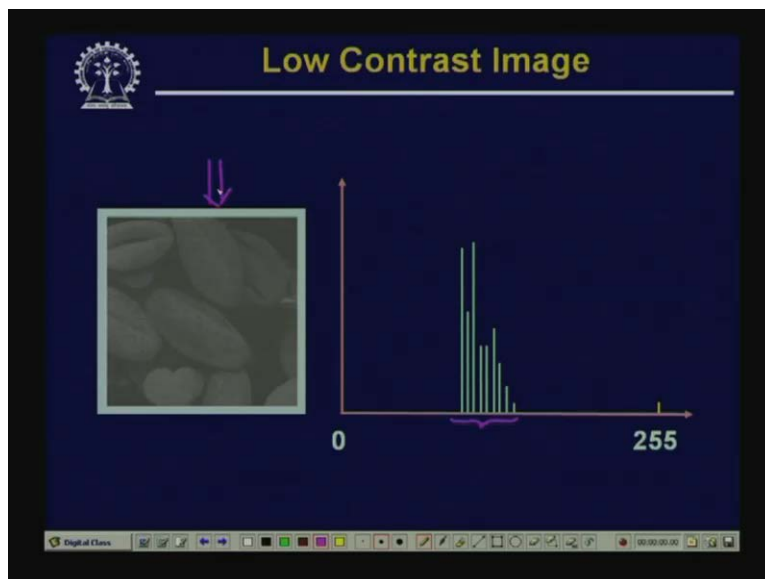
So here, this particular image because we are considering all the images which are digitized and every pixel is digitizing digitized even 8 bits; so we will have total 256 number of intensity levels and those 256 number of intensity levels are represented by intensity values from 0 to 255 and for this particular case, for this particular dark image, you find that most of the pixels have intensity values which are near to 0 and that gives a very very dark appearance of this image. Now, let us see a second image.

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Here, you find that this image is very bright and if you look at the histogram of this particular image; you find that for this image, the histogram shows that most of the pixels of this image have intensity values which are near to the maximum that is near value 255 and because of this the image becomes very bright. Let us come to a third image category.

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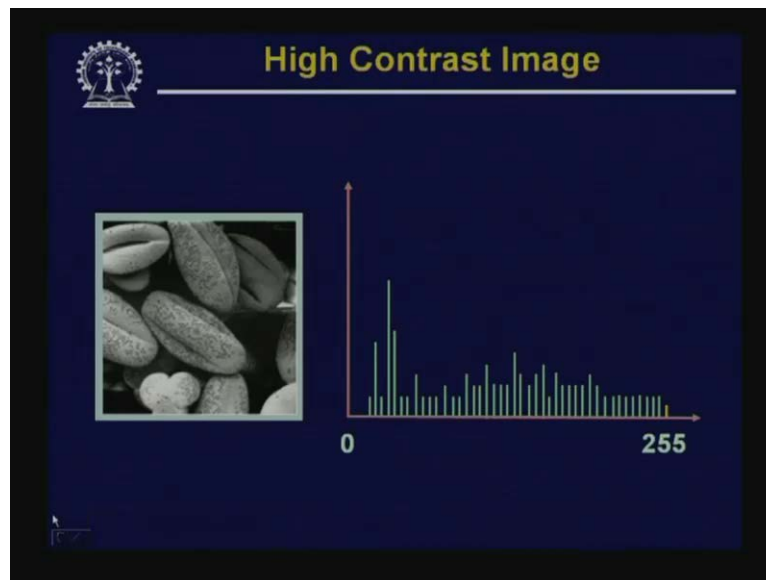


This is an image where you find that the intensity values are higher than the intensity values of the first image that you had shown. It is lower than the intensity values of the just previous image that we have shown. So, this is something in between and the histogram of this particular image shows that most of the pixels of this image have intensity values which are in the middle range

and not only that, the **spade** of the intensity values of this pixels are also very low, the **spade** is very very small.

So, this image appears to be a medium kind of image, it is neither very dark nor very bright. So, the image is a medium kind of image but at the same time, the variation of the intensity values of this particular image is very poor and as a result, the image that we have got over here; this image gives a medium kind of appearance, not very bright neither very low but at the same time, the variation of intensities is not very clear. That means the contrast of the image is very very poor. So, let us look at the fourth category image.

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So this one, in this image, the histogram plot shows that the intensity values vary from very low value to very high value that is it has a wide variation from 0 to 255 levels and as a result, the image appears to be a very very prominent image having low intensity values, high intensity values and at the same time, if you look at the image, you find that many of the details of the image are easily visible from this particular image.

So, as we said that the histogram, the nature of the histogram shows that what is the global appearance **of the image** of an image and which is also quite obvious from these 4 different types of images that we have shown; the first one was the gray image which is a dark image, the second one was bright image, the third one was a medium category image but the contrast of the image was very poor and we will see that this fourth one is an ideal image at least for the visualization purpose where the image brightness is proper and at the same time, the details of the objects present in the image can also be very easily understood. So, this is an image which is a high contrast image.

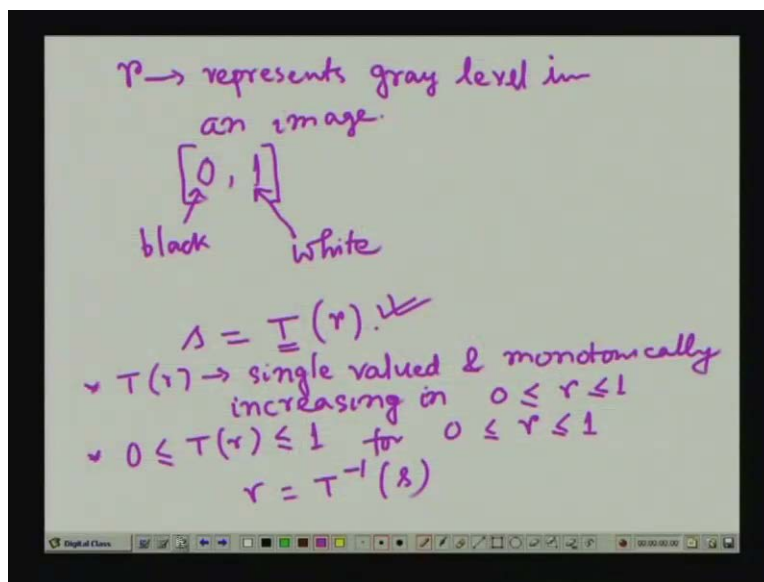
So, when we talk about this histogram based processing, most of the histogram based image enhancement techniques, they try to improve the contrast of the image; whether we talk about the histogram equalization or the histogram modification techniques.

Now, when we talk about this histogram based techniques, this histogram based techniques; the histograms just give you a description a global description of the image. It does not tell you anything about the content of the image and that is quite obvious in these cases. Just by looking at the histogram, we cannot say that what is the content of the image.

We can just have an idea of what is the global appearance of that particular image and histogram based techniques try to modify this histogram of an image to have an image to appear in a particular way; either dark or bright or the image contrast is very high and depending upon the type of operations that we do using these histograms, we can have either histogram equalization operation or we can have histogram modification operation.

So now, let us see that once we have given that what is a histogram and what does the histogram tell us, let us see that how these histograms can be processed to enhance the images. So, the first one that we will talk about is the image equalization or histogram equalization operation.

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So, for this histogram equalization operation, initially we will assume that r to be a variable representing the gray level in an image. So, this r represents the gray level in an image and for the time being, we will also assume that the pixel values in an image are continuous and they are normalized in the range 0 to 1. So, we assume the normalized pixel values and the pixel values can take values in the range 0 to 1 where 0 indicates a black pixel, so 0 indicates a black pixel and 1 indicates a white pixel.

Later on, we will extend our ideas to discrete formulation when we will consider the pixel values in the range 0 to capital L minus 1 where L is the number of gray level, discrete gray levels present in the image. Now, as we said that for point possessing, we are interested to find out a transformation where the transformation is of the form s is equal to $T(r)$ where r is the intensity

in the original image and s is the intensity in the process remains or the transformed image or the enhanced image.

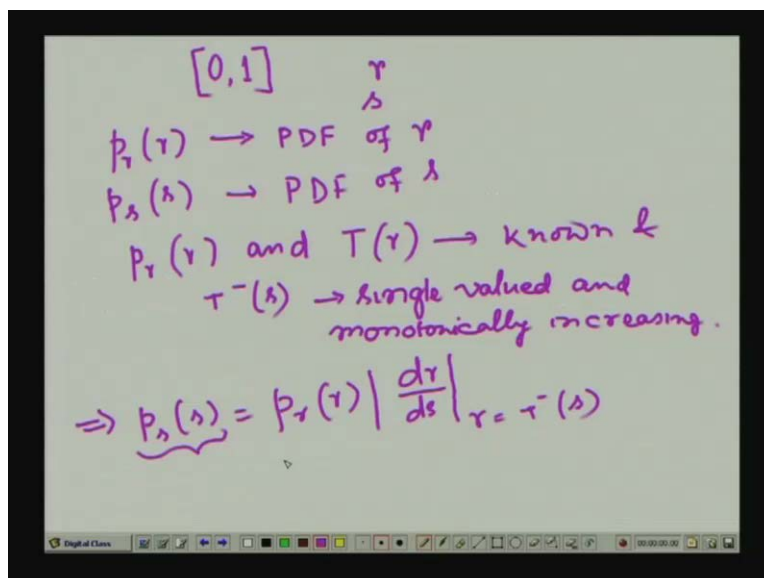
Now this T , the transformation function has to satisfy 2 conditions. Firstly the $T(r)$ has to be single valued and it has to be a monotonically increasing in the range 0 to 1. So, the first condition is $T(r)$, it must be single valued and monotonically increasing in the range 0 less than or equal to r less than or equal to 1 and the second condition that $T(r)$ must satisfy is 0 should be less than or equal to $t(r)$ which should be less than or equal to 1 for 0 less than or equal to r less than or equal to 1.

Now, the first condition is very very important because it maintains the order of the gray levels in the processed image. That is a pixel which is dark in the original image should remain darker in the processed image; a pixel which is brighter in the original image should remain brighter in the processed image. So, the intensity ordering does not change in the processed image and that is guaranteed by the first condition that is $T(r)$ should be single valued and monotonically increasing in the range 0 to 1 of the values of the r . The second condition that is 0 less than or equal to $T(r)$ less than or equal to one this is the one which ensures that the processed image that you get, that does not leads to a pixel value which is higher than the maximum intensity value that is allowed.

So, this ensures that the processed image will have pixel values which are always within the available minimum and maximum range and it can be found that if these conditions are satisfied by $T(r)$; then the inverse that is r is equal to T inverse of s will also satisfy these 2 conditions. So, we want a transfer function T which will satisfy these conditions and if these conditions are satisfied by $T(r)$, then the inverse transformation will also satisfy this particular condition.

Now, let us say how the histograms help us to get a transfer function function of this form?

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So now, we assume, so as we said that we assume that the images assume the intensity values, normalized intensity values in the range 0 to 1 and as we said that r is an intensity value in the original image, s is an intensity value in the processed image. We assume $p_r(r)$ to be the probability density function of r where r is the variable representing intensity values in the original image and we also assume $p_s(s)$ to be the PDF or probability density function of s where s is a variable representing intensity values in the processed image. So, these are the 2 probability functions PDFs that we assume.

Now given this, from elementary probability theory we know that if $p_r(r)$ and the transformation function $T(r)$, they are known and T inverse s is single valued and monotonically increasing, T inverse s is single valued and monotonically increasing. Then we can obtain the PDF of s that is $p_s(s)$ is given by $p_r(r)$ into $dr ds$ where at r equal to T inverse s .

So, this is what is obtained from elementary probability theory that if we known $p_r(r)$ and we also know $T(r)$ and T inverse s , a single valued and monotonically increasing; then $p_s(s)$ can be obtained from $p_r(r)$ as $p_s(s)$ is equal to $p_r(r)$ into $dr ds$.

Now, all the histogram processing techniques, they try to modify the probability density function, PDF $p_s(s)$ so that the image gets a particular appearance and this appearance is obtained where the transformation function $T(r)$. So now, what is that type of $T(r)$, the transformation function $T(r)$ that we can have? So, let us consider a particular transformation function.

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$$s = \underline{T(r)} = \int_0^r p_r(\omega) d\omega \quad 0 \leq r \leq 1.$$

$$\frac{ds}{dr} = p_r(r).$$

$$\Rightarrow p_s(s) = p_r(r) \left| \frac{dr}{ds} \right|$$

$$= p_r(r) \cdot \frac{1}{p_r(r)}$$

$$= 1$$

Say, we take a transformation function of this form say s is equal to $T(r)$ is equal to integral $p_r(\omega) d\omega$ where the range of integration varies from 0 to r and r varies in the range 0 to 1. So, we find that this integral gives the cumulative distribution function of the variable r . Now, if I take $T(r)$ of this particular form, then this particular $T(r)$ will satisfy all the conditions, both the

conditions that we have stated earlier. And from this, we can compute ds upon dr which is nothing but $p_r(r)$.

So, by substitution in our earlier expression, you find that $p_s(s)$ as we have said is nothing but $p_r(r)$ into $dr ds$, this we have said earlier, this is obtained from elementary probability theory and in this particular case, this will be $p_r(r)$ into 1 upon $p_r(r)$ which will be equal to 1. So, we find that if we take this particular transformation function which is nothing but cumulative distribution function of the variable r ; then using this transformation function, the transformation that we get generates an image which has a uniform probability density function of the intensity values s .

And, we have seen earlier that an image, high contrast image have a probability distribution function or has a histogram which has **intensity values** pixels having intensity values over the entire range 0 to 255 of the pixel values. So, if I go for this kind of transformation, as we are getting an uniform probability distribution function, probability density function of the processed image; then this is expected, then this is what is going to enhance the contrast of the image and this particular result is very very important that $p_s(s)$ is equal to 1 and you find that we have obtained this result irrespective of $T^{-1}(s)$ and that is very very important because it may not always be possible to obtain T^{-1} analytically.

So, whatever be the nature of $T^{-1}(s)$, if we take that cumulative distribution function of r and use that as the transformation function $T(r)$; then the image is going to be enhanced. So, this simply says that using CDF, the cumulative distribution function as the transformation function, we can enhance the contrast of an image and by this contrast enhancement what you mean is the dynamic range of the intensity values is going to be enhanced.

Now, what we have discussed till now, this is valid for the continuous domain. But the images that we are going to consider, all the images are discrete image. So, we must have a discrete formulation of whatever derivation that we have done till now.

So now, let us see that how we can have a discrete formulation of these derivations.

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The image shows a whiteboard with handwritten mathematical formulas in purple ink. The formulas are as follows:

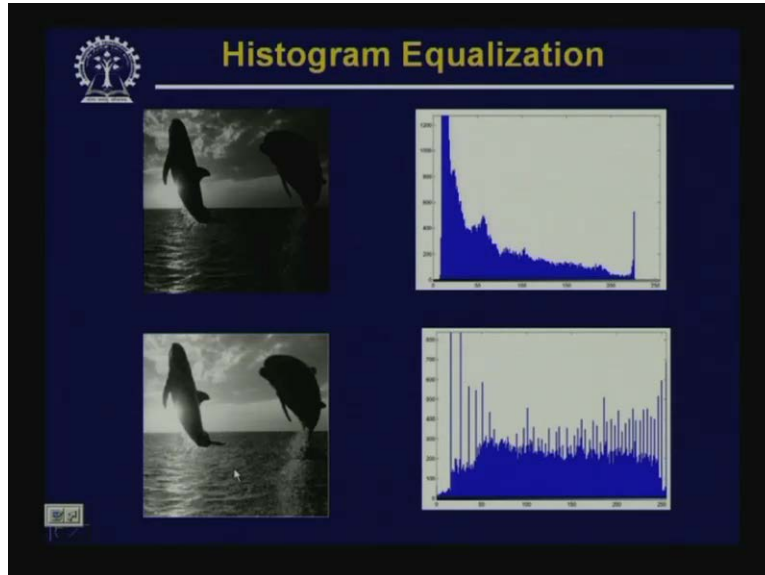
$$p_r(r_k) = \frac{n_k}{n}$$
$$s_k = T(r_k) = \sum_{i=0}^k p_r(r_i)$$
$$= \sum_{i=0}^k \frac{n_i}{n}$$
$$r_k = T^{-1}(s_k) \quad 0 \leq s_k \leq L$$

So, for discrete formulation, what we have seen earlier is that $p_r(r_k)$ is given by n_k divided by n where n_k is the number of pixels having intensity value r_k and n is the total number of pixels in the image. And a plot of this $p_r(r_k)$ for all values of r_k gives us the histogram of the image. So, the technique to obtain the histogram equalization and by that the image enhancement will be; first we have to find out the cumulative distribution function the CDF of r_k and so we will get s_k which is given by $T(r_k)$ and this $T(r_k)$ now is the cumulative distribution function which is p_r of say r_i where i will vary from 0 to k and this is nothing but sum of n_i by n where i will vary from 0 to k . The inverse of this is obviously r_k is equal to T inverse of s_k for 0 less than or equal to s_k less than or equal to 1 .

So, if I use this as a transformation function, then the operation that we get is an histogram equalization and as we have said that this histogram equalization basically gives us a transformed image where the intensity values have an uniform distribution and because of this, the image the processed image that we get appears to be a high contrast image.

So, let us see that what are the results that we can get using such a kind of histogram equalization operation?

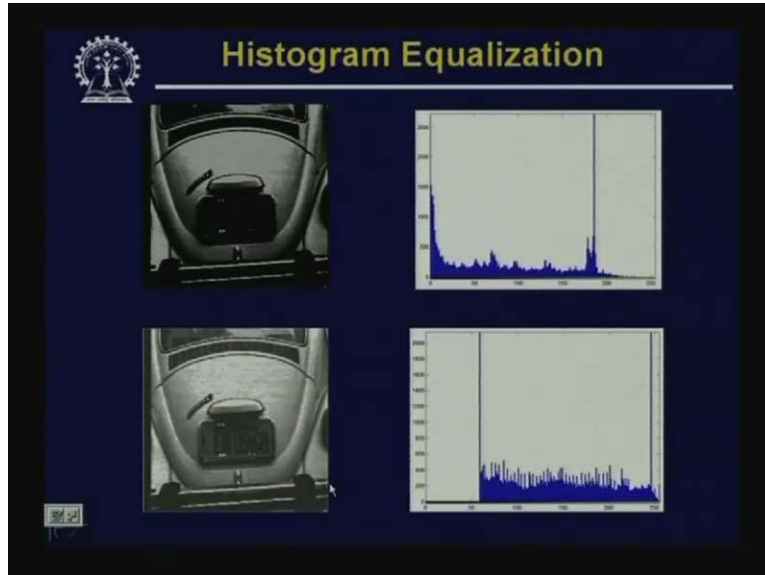
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So here, on the left hand side, we have an image and it is obvious that the contrast of this image is very very poor. On the right hand side we have shown the histogram of this particular image and here again you find that from this histogram that most of the pixels in this particular image have intensities which are very close to 0 and there are very few pixels in this image which are intensities having higher values.

By this histogram equalization, the image that you get is shown on the bottom and here you find that this image obviously has a contrast which is higher than the previous image because many of the details in the image are not very clear in the original image whereas those details are very clear in this second image and on the right hand side, we have shown the histogram of this processed image and if you compare these 2 histograms, you will find that the histogram of this processed image is **more of equalization** we can have such a kind of enhancement.

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This shows another image, again processed by histogram equalization. So on the top, you find that this is the image of a part of a car and because of this enhancement, not only the image appears to be better but if you look at this number plate; you find that in the original image, the numbers are not readable whereas in this processed image I can easily read this number say something like FN 0968. So, this is not readable in the original but it is readable in the processed image and the histogram that I get of this particular image which is almost **which is** near to be uniform.

So, this is one kind of histogram based processing technique that is histogram equalization which gives enhancement of the contrast obtained. Now, though this gives an enhancement, it gives contrast enhancement but histogram equalization has got certain limitation. First of the limitation is using this histogram equalization; whatever image you get, the equalized image you get that is fixed. I cannot have any interactive manipulation of the image.

So, it generates only single processed image. Now, to overcome this limitation if some of the applications, if some application demands that we want to enhance only certain region of the histogram, we want to have the details within certain region of the histogram; note what is given by the histogram equalization process, then the kind of technique that should be used is what is called histogram matching or histogram specification techniques.

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Target Histogram.

$r \rightarrow p_r(r) \Rightarrow \text{input image}$
 $z \rightarrow \underline{p_z(z)}$
 $s = T(r) = \int_0^r p_r(\omega) d\omega$
 $G(z) = \int_0^z p_z(t) dt$
 $G(z) = T(r) = s$
 $\underline{z} = G^{-1}(s) = G^{-1}[T(r)]$

So in case of histogram specification techniques, what we have to have is we have to have a target histogram. So, we have to have a target histogram and the image has to be processed in such a way that the histogram of the processed image becomes same as that of the target histogram.

Now, to say how we can go for such a type of histogram specification or histogram matching or histogram modification; initially, we assume that we have again we have 2 variables. One is variable r representing the continuous gray levels in the given image and we assume a variable z representing intensities in the processed image. r is the intensities in the original image and z represents the intensities in the processed image where this is specified in the form of the probability distribution function $p_z(z)$. So, this $p_z(z)$ specifies r target histogram and from the given image r , we can obtain $p_r(r)$ that is the histogram of the given image. So, this we can obtain from the input image whereas $p_z(z)$ that is target histogram is specified.

Now, for this histogram matching, what we have to do is if I equalize the given image using the transformation function s is equal to $T(r)$ as we have seen earlier is equal to $\int_0^r p_r(\omega) d\omega$ within range 0 to r ; so if I equalize the given image using this particular transformation function, then what I get is an image having intensity values with probability distribution function, probability density function which is uniform.

Now, using this $p_z(z)$, we compute the transformation function $G(Z)$. So, this $G(Z)$ will be obtained as integration $p_z(z)$ sorry $p_z(t)$ into dt in the range 0 to z and then from these 2 equations, what we can have is $G(z)$ is equal to $T(r)$ that is equal to s and this gives Z equal to G inverse s which is equal to G inverse $T(r)$.

So, you find that the operations that we are doing is firstly, we are equalizing the given image using histogram equalization techniques, we are finding out the transformation function $G(z)$ from the histogram from the target histogram that has been specified, then this equalized image

is inverse transformed using the inverse transformation G^{-1} and the resultant image by doing this operation, the resultant image that we will get that is likely to have an histogram which is given by this target histogram $p_z(z)$.

So, our procedure is; first equalize the original image obtaining the histogram from the given image, then find out the transformation function $G(z)$ from the target histogram that has been specified, then do the inverse transformation of the equalized image using not T^{-1} but using the G^{-1} and this G^{-1} has to be obtained from the target histogram that has been specified and by doing this, the image that you get becomes an histogram modified image, a processed modified image, processed image whose histogram is likely to be same as the histogram that has been specified as the target histogram.

So, again this is a continuous domain formulation but our images are digital, so we have to go for a discrete formulation of these derivations. So now, let us see that how we can this particular formulation.

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$$s_k = T(r_k) = \sum_{i=0}^k \frac{n_i}{n} \Rightarrow \text{from the input image.}$$

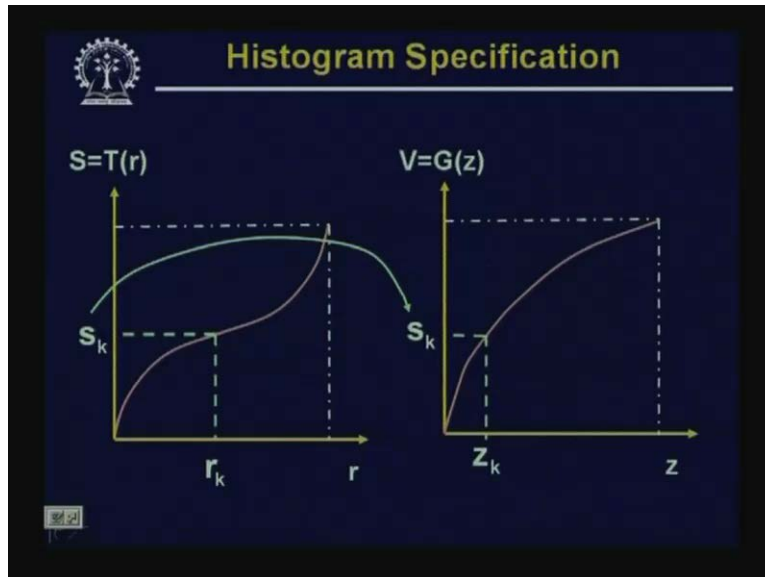
$$v_k = G(z_k) = \sum_{i=0}^k p_z(z_i) = s_k \quad k=0, 1, \dots, L-1$$

$$z_k = G^{-1}[T(r_k)]$$

So again, as before we can find out s_k which is equal to $T(r_k)$ which is equal to sum of n_i by n where n varies from 1 to n where r varies from, i varies from 0 to k and this we obtained from the given image, from the input image and from the target histogram that is specified that is $p_z(z)$, we get a transformation function say v_k equal to $G(z_k)$ which is equal to sum of $p_z(z_i)$ where now i varies from 0 to k and we set this equal to s_k and this has to be for k equal to $0, 1$ upto L minus 1 and then finally we obtain the processed image as the inverse of or G^{-1} of $T(r_k)$.

So, this is the discrete formulation of the continuous domain derivations that we have done earlier. Now, let us see that using this, what kind of operations that we have.

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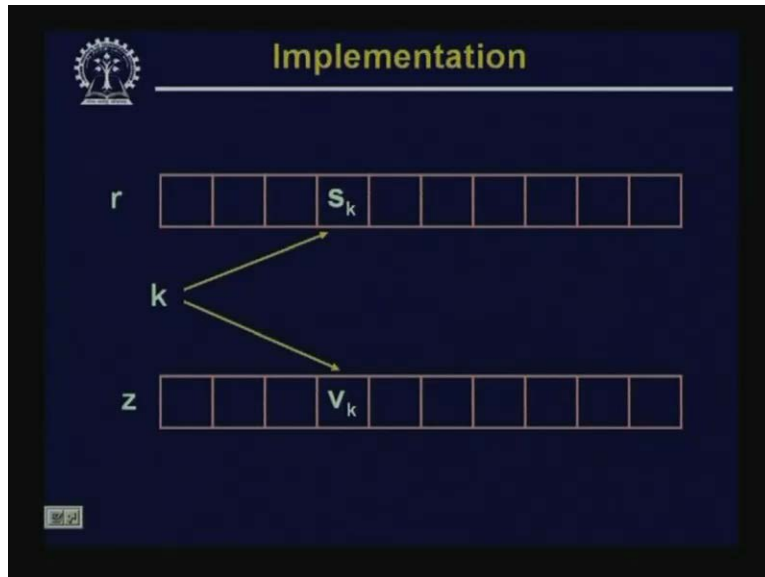
So here, it shows a transformation function $T(r)$ is equal to $T(r)$ on left hand side which is obtained from the given image and using the target histogram, we obtain the function $G(z)$. So, this function $T(r)$ gives the value S_k for a particular intensive value r_k in the given image. The function $G(z)$, it is supposed to give an output value V_k for an input value Z_k .

Now coming $G(z)$, you find that Z_k is the intensity value which is not known to us. We want to find out Z_k from r_k . So, the operation that will be doing for this is whatever S_k that we get from r_k , we set that S_k to this second transformation and now you do the inverse transformation operation. So, as shown in the next slide, we set S_k along the vertical axis of this V equal to $G(z)$ transformation function, then you do the inverse transformation that is from S_k you come to Z_k . So, what we have to apply is an inverse transformation function to get the value Z_k for a given intensive value r_k in the original image.

Now, conceptually or graphically, this is very simple. But the question is how to implement it? Here we find that in the continuous domain, we may not get analytical solutions for G inverse. But in the discrete domain, the problem becomes simpler because we are considering we are dealing with only discrete values.

So, in case of discrete domain, this transformation function that is r_k to s_k or S equal to T of r or Z_k to V_k that is V equal to $G(z)$, these transformations can be implemented by simple look of tables. So, by this what I mean is something like this.

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$T(r)$ is represented by an array where for r_k , the k indicates an index into an array and the element in that particular array location gives us the value S_k . So, whenever a value r_k is specified using k , immediately go to this particular array r and the content of that array location gives us what is the corresponding value S_k .

Similarly, for V equal $G(z_k)$, V_k equal to $G(z_k)$; we have similar operation that if Z_k is known, I can use k as an index, go to the array z , then I get the corresponding value V_k . Now, in the first case, it is very simple; I know what is the value of r_k , so I can find out what is the corresponding value of S_k from this array but the second one is an inverse operation. I know S_k or as we have equated S_k to V_k , I know what is V_k . Now, from this V_k , I have to find out what is the corresponding value Z_k . So, this is an inverse problem and to solve this problem, we have to go for an iterative solution approach.

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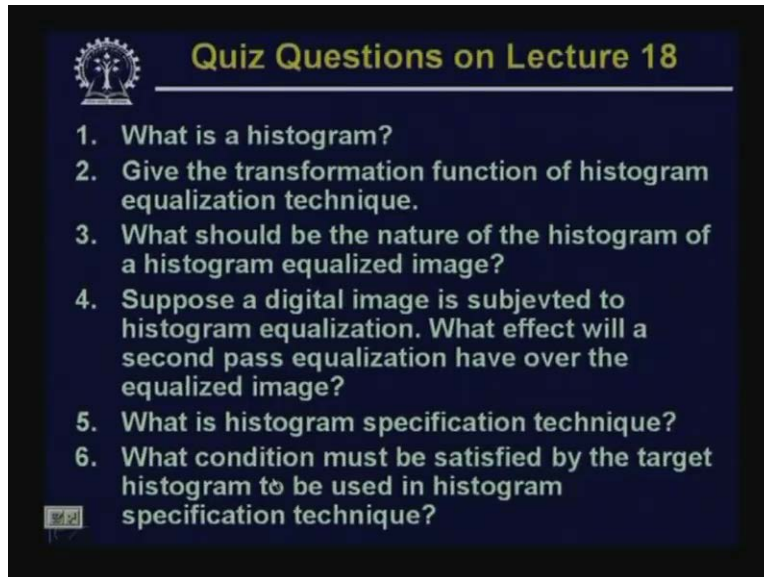
The image shows a whiteboard with handwritten mathematical notes. At the top, it states $G(z_k) = S_k$. Below this, it says $\Rightarrow G(\hat{z}_k) - S_k = 0 \quad k=0, 1, \dots, L-1$. An arrow points from \hat{z}_k to the text "smallest integer". Below that, it says $G(\hat{z}) - S_k \geq 0$ with a bracket underneath. At the bottom, it says $z_k \approx S_k$. At the very bottom of the whiteboard, there is a software toolbar with various icons and a timestamp of 09:00:00.

So, an iterative solution, we can obtain in this form. We know that $G(z_k)$ is equal to S_k . So, this gives $G(z_k)$ minus S_k , this is equal to 0. So, our approach will be to iterate on the values of Z_k to get a solution on this and this has to be done for k equal to 0, 1 upto L minus 1. So, what we should do?

The closest solution can be that we initialize z to a value say Z hat. So, we initialize Z_k is equal to Z hat for every value of k where this Z hat is the smallest integer, **Z hat is the smallest integer** which satisfies $G(z)$ hat minus S_k greater than or equal to 0. So, our approach can be that we start with a very small value, the smallest integer of Z hat, then go on incrementing Z hat by 1 at every step until and unless this condition is satisfied. So, when this condition is satisfied, then the value of Z hat will get that is the Z_k corresponding to this given value S_k .

So now, let us stop our discussion today. We will continue with this topic in our next class.

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The slide features a dark blue background with a white logo in the top left corner. The title "Quiz Questions on Lecture 18" is written in yellow at the top. Below the title, a list of six questions is presented in white text. A small navigation icon is visible in the bottom left corner of the slide.

Quiz Questions on Lecture 18

1. What is a histogram?
2. Give the transformation function of histogram equalization technique.
3. What should be the nature of the histogram of a histogram equalized image?
4. Suppose a digital image is subjected to histogram equalization. What effect will a second pass equalization have over the equalized image?
5. What is histogram specification technique?
6. What condition must be satisfied by the target histogram to be used in histogram specification technique?

Now, coming to the questions of today's lectures; the questions are first, what is a histogram? Give the transformation function of histogram equalization technique? What should be the nature of the histogram of a histogram equalized image? Suppose, a digital image is subjected to histogram equalization, what effect will a second pass equalization have over the equalized image? What is histogram specification technique? What condition must be satisfied by the target histogram to be used in histogram specification technique?

Thank you.

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The slide is a solid black rectangle with the text "Preview of next lecture" centered in a large, white, sans-serif font.

Preview of next lecture

Hello, welcome to the video lectures series on digital image processing. For last few classes, we have started our discussion on image enhancement techniques.

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So, in the previous class, we have seen what is meant by histogram; we have seen how the global appearance of an image is reflected in its histogram, we have seen that histogram based enhancement techniques aims at modifying the global appearance of an image by modifying its histogram. Then we have started discussion on histogram equalization technique and histogram specification or histogram matching techniques.

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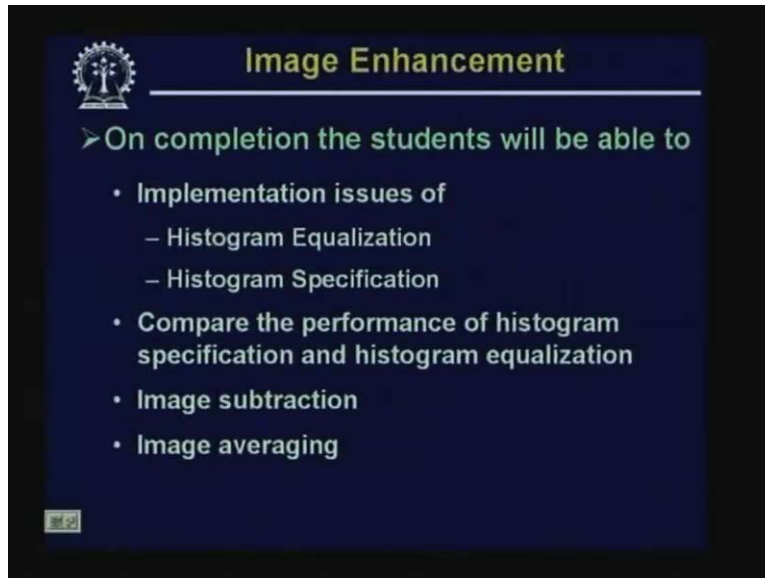


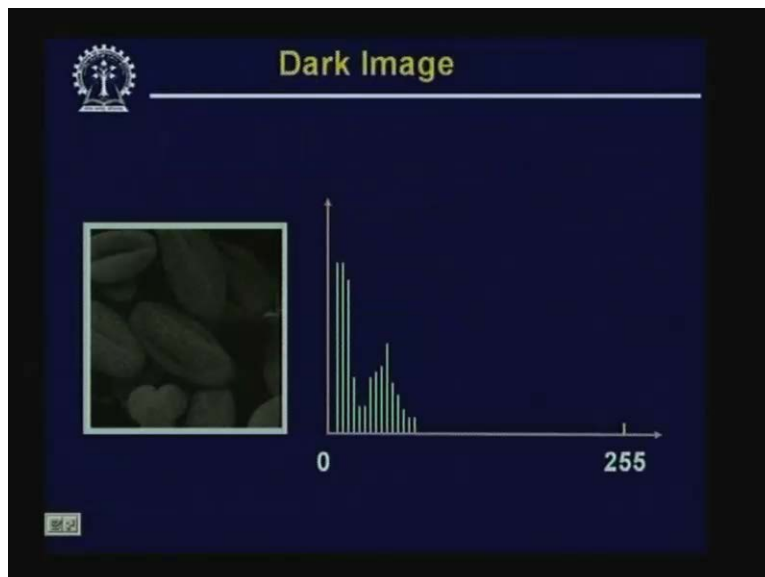
Image Enhancement

➤ On completion the students will be able to

- Implementation issues of
 - Histogram Equalization
 - Histogram Specification
- Compare the performance of histogram specification and histogram equalization
- Image subtraction
- Image averaging

So today's class, we will talk about some implementation issues of histogram equalization and histogram specification techniques and we will talk about this implementation issues with respect to some examples. Then we will also compare the performance of histogram specification and histogram equalization techniques with the help of some results obtained on some images. Then lastly, we will talk about two more point processing techniques for histogram equalization; one of them is histogram subtraction and other one is histogram averaging techniques. So now, let us briefly recapitulate what we have done in the last class.

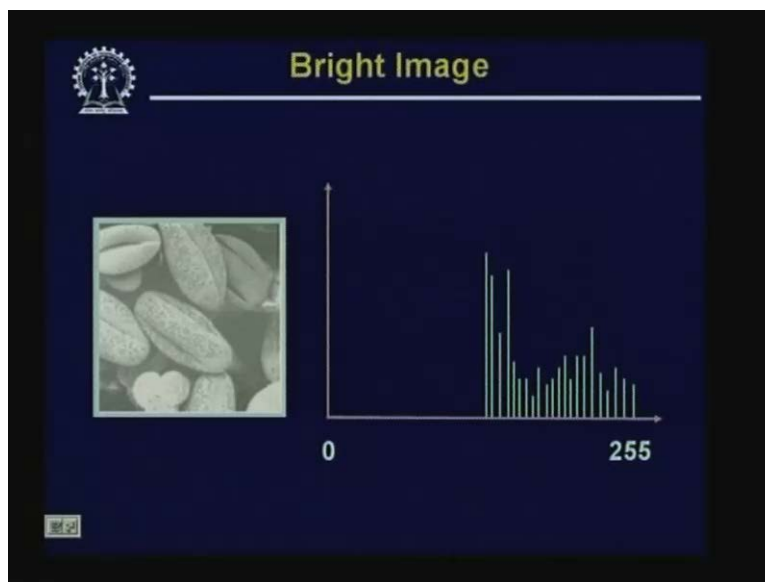
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As we have said that histogram of an image that indicates what is the global appearance of an image. We have also seen these images in the last class but just for a quick recapitulation; you will find that on the left hand side, we have shown an image which is very dark and we call this

as the dark image and on the right hand side, we have shown the corresponding histogram and you will find that this histogram shows that most of the pixels in this particular image, they are having an intensity value which is near about 0 and there is practically no pixel having higher intensity values and that is what gives this particular image a dark appearance.

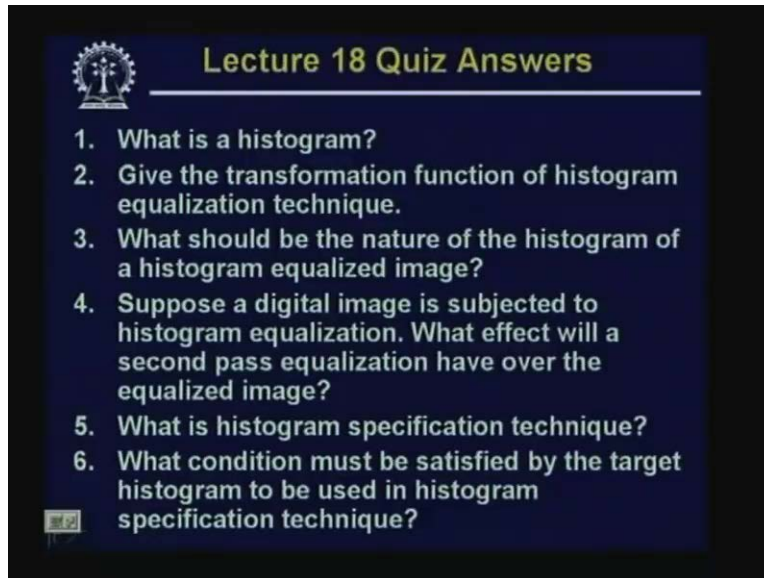
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Then the second one that we have shown is a bright image or a light image and again from this particular histogram, you will find that most of the pixels in this particular image have intensity values which are near to maximum value that is 255 in this particular case and since we are talking about all the images in our application which are quantized where every pixel is quantized with 8 bits, so the intensity levels will vary from 0 to the 255.

So, in our case, the minimum intensity of a pixel will be 0 and the maximum intensity of a pixel will be 255. So, in this particular example, you will find that the intensity of the images as this histogram shows that most of the pixels have intensity which are ... ((55:50))

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What **is the effect** what effect will a second pass equalization have over the equalized image? So, as we have already mentioned that once an image is histogram equalized, the histogram of the processed image will be a uniform histogram. That means it will have a uniform probability density function and if I want to equalize this equalized image, then you will find that the corresponding transformation function will be a linear one where the state line will be inclined at an angle of 45 degree with the x axis.

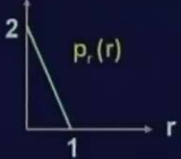
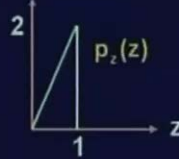
So, that clearly indicates that whatever kind of equalization you do over an already equalized image. That is not going to have any further effect on the processed image. So, this is ideal case but practically we have seen that after equalization, the histogram that you get is not really uniform. So, there will be some effect in the second pass **the effect** but the effect may be negligible.

Sixth one is again a tricky one. What condition must be satisfied by the target histogram to be used in histogram specification technique? You will find that in case of histogram specification technique, the target histogram is used for inverse transformation that is G^{-1} . So, **it must be** it must be true that the transformation function G has to be monotonically increasing and that is only possible if you have the value of $p_z(z)$ non 0 for every possible value of z . So, that is the condition that must be the satisfied by the target histogram.

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Quiz Questions on Lecture 19

1. Explain why the discrete histogram equalization technique does not, in general, yield a flat histogram.
2. An image has gray level PDF $p_r(r)$ as shown in the following diagram. The transformation function should transform the gray levels so that they will have the specified $p_z(z)$. Find the transformation in terms of r and z .

Now, coming to today's questions; first one is explain why the discrete histogram equalization technique does not in general yield a flat histogram. The second, an image has a gray level PDF $p_r(r)$ as shown here and the target histogram as shown on the right. We have to find out the transformation in terms of r and z that is what is the mapping from r to z .

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Quiz Questions on Lecture 19

3. Given $X_i = Y_i = 0, 1, 2, 3$; $p_r(x_i) = 0.25, i = 0, \dots, 3$
 $p_z(y_0) = 0, p_z(y_1) = p_z(y_2) = 0.5, p_z(y_3) = 0$. Find the transformation between r and z .

The third question we have given the probability density functions to probability density functions, again you have to find out the transformation between r and z .

Thank you.