Digital Image Processing

Prof. P. K. Biswas

Department of Electronic & Electrical Communication Engineering

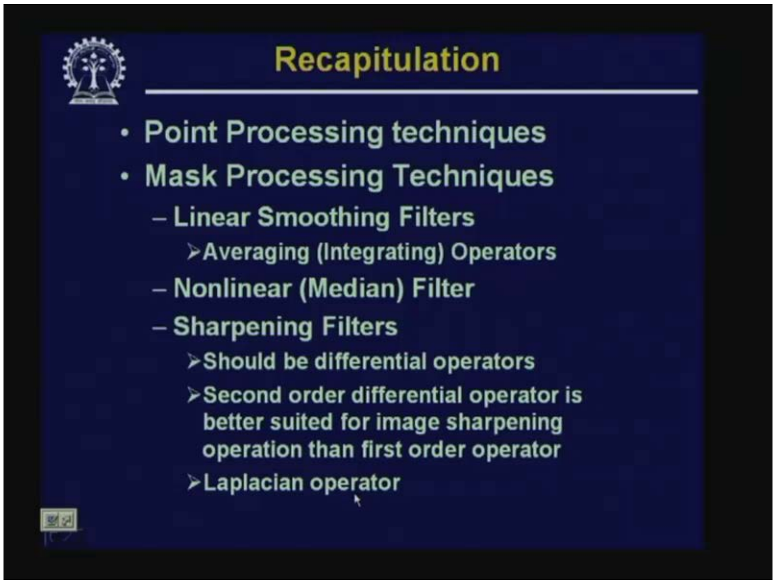
Indian Institute of Technology, Kharagpur

Lecture - 21

Image Enhancement Frequency Domain Processing

For last few lectures, we are talking about image enhancement techniques specifically the spatial domain techniques for image enhancement.

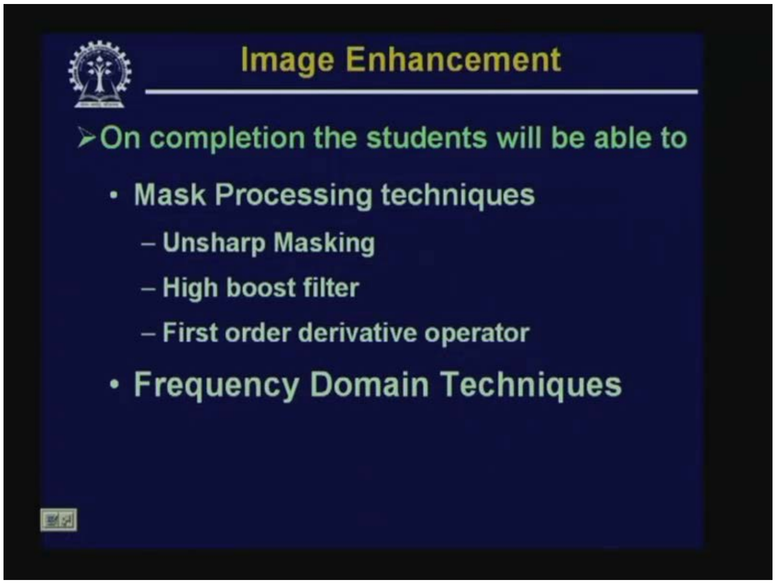
(Refer Slide Time: 00:29)



So, for last few lectures, we have talked about the point processing techniques and we have talked about few mask processing techniques for image enhancement. Both point processing techniques as well as mask processing techniques, we have said that they are spatial domain techniques in the sense that they walk directly on the image pixels.

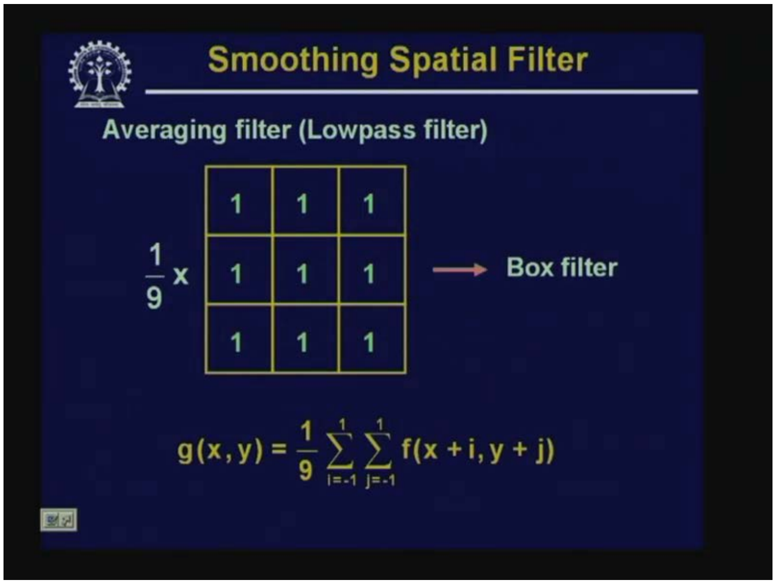
So, among the mask processing techniques, what we have done so far is we have talked about the linear smoothing filters or averaging filters and we have seen that this smoothing or averaging filters are some sort of integration operation which integrates the image pixels. We have also talked about a non linear filter or a filter based on ordered statistics which we have said is the median filter and we have talked about a sharpening filter and we have said that this sharpening filter is nothing but some sort of differential operators which differentiate the image pixels to sharpen the image and we have said that for such sharpening operation, the kind of derivatives which are most suitable is the second order derivative and accordingly, we have discussed about the second order derivative operators which we have said as Laplacian operator and we have demonstrated with results that how this Laplacian operators in the spatial domain, they try to enhance the content of an image.

(Refer Slide Time: 2:14)



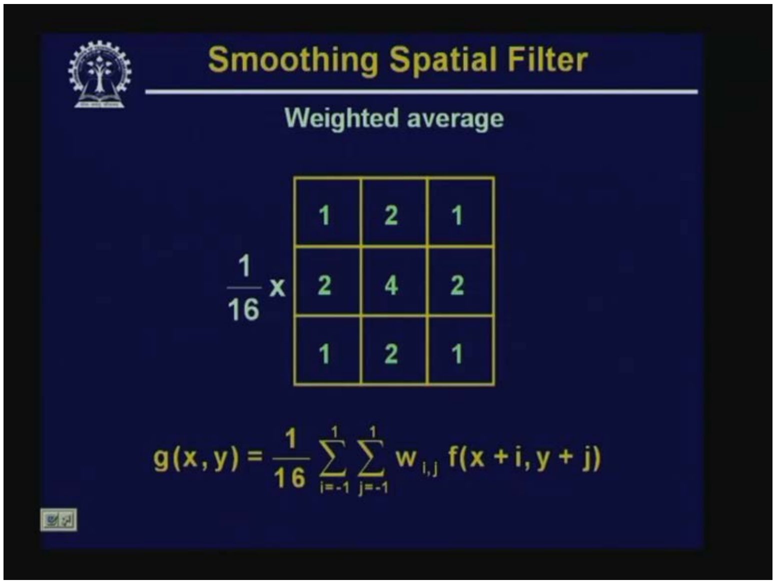
So today, we will talk about some more mask processing techniques like; we will talk about un sharp masking, we will talk about high boost filter and we will also see that how the first order derivative operators can help in enhancement of image content particularly at the discontinuities and age regions of an image and then we will go to our today's topic of discussion which we say is the frequency domain techniques for image enhancement and here again, we will talk about various types of filtering operations like low pass filtering, high pass filtering, then equivalent to high boost filtering and then finally, we will talk about homomorphic filtering and all these filtering operations will be in the frequency domain operations. So, let us first quickly see that what we have done in the last class.

(Refer Slide Time: 3:06)



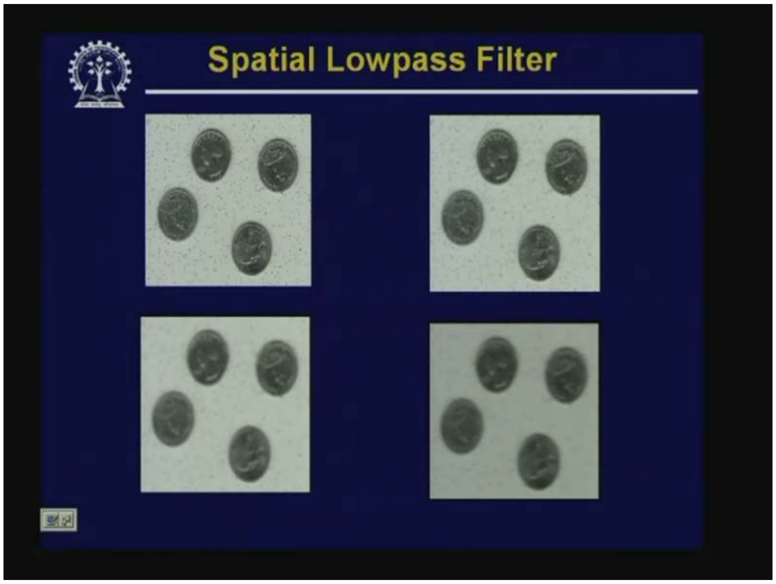
So in the last class, we have talked about the averaging filters or low pass filters and we have talked about 2 types of spatial masks which are used for this averaging operations. One, we have said as box filter and we have said that in case of box filter, all the coefficients in the filter mask, they have the same value and in this case, all the coefficients have value equal to 1.

(Refer Slide Time: 3:36)



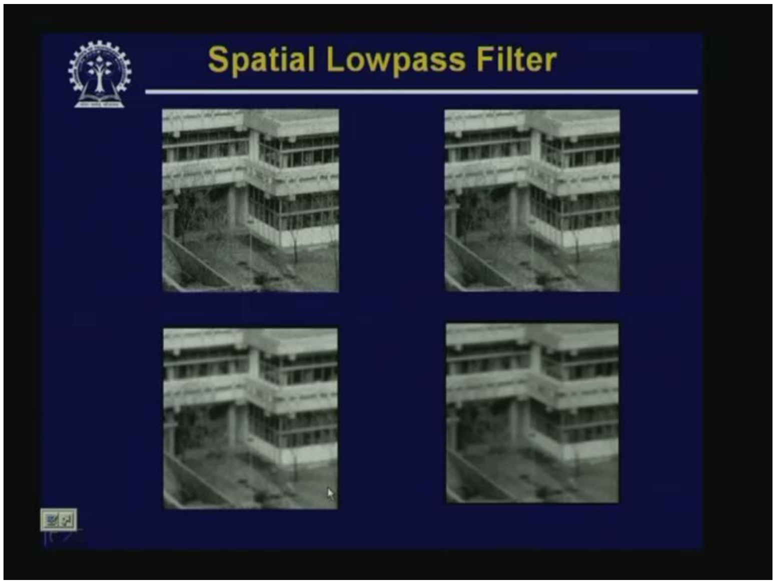
The other type of mask that we have used is for weighted average operation and here it shows the corresponding mask which gives the weighted averaging and we have said that if you use this weighted averaging mask instead of the box filtered mask, then what advantage we get is this weighted average mask tries to retain the sharpness of the image or the contrast of the image as much as possible whereas if we simply use the box filter, then the image gets blurred too much.

(Refer Slide Time: 4:09)



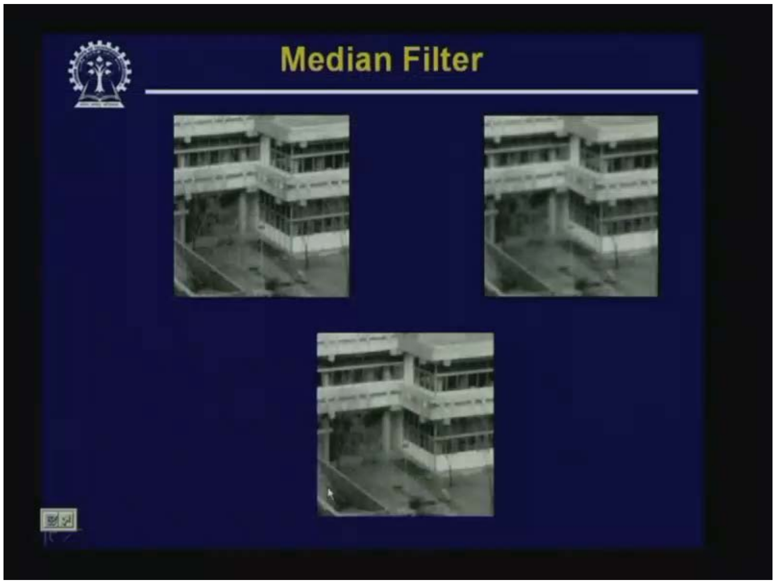
Then these are the different kinds of results that we have obtained. Here, the result is shown for an image which is on the top left. On the top right, the image is averaged by a 3 by 3 box filter; on the bottom left, this is an averaging over 5 by 5 filter and on the bottom right, this is an image with averaging over 7 by 7 filter and as it is quite obvious from this results that as we take the average or smooth out the image with the help of this box filters, the images get more and more blurred. Similar such results are also obtained and have been shown in this particular case.

(Refer Slide Time: 4:52)



Here also you find that using the low pass filter, the content, the noise in the image gets removed but at the cost of the sharpness of the image. That is when we take the average over a larger mask, a larger size mask; then it helps to reduce the noise but at the same time, a larger mask introduces large amount of blurring in the original image.

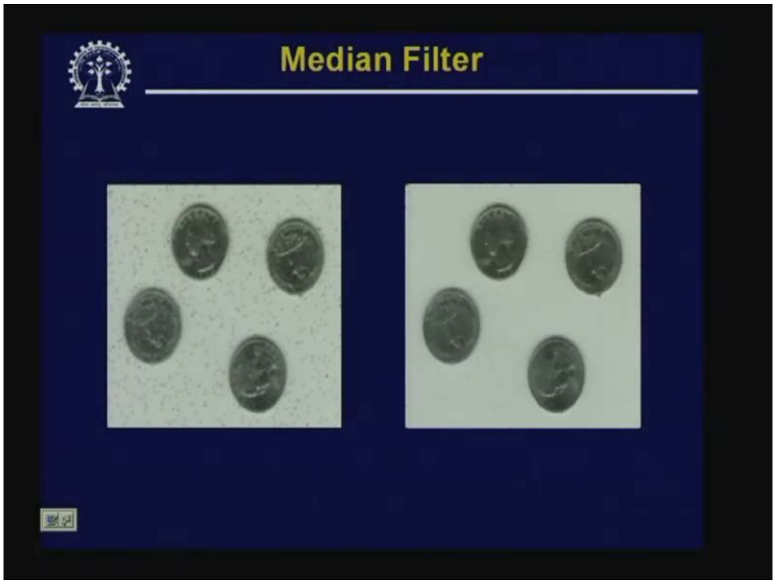
(Refer Slide Time: 5:19)



So, there we have said that instead of using simple box filter or the simple averaging filter if I go for order statistics, go for filtering based on order statistics like median filter or the pixel value at a particular location in the processed image will be the median of the pixels in the neighborhood of the corresponding location in the original image; in that case, this kind of filtering also reduces the noise. But at the same time, it tries to maintain the contrast of the image.

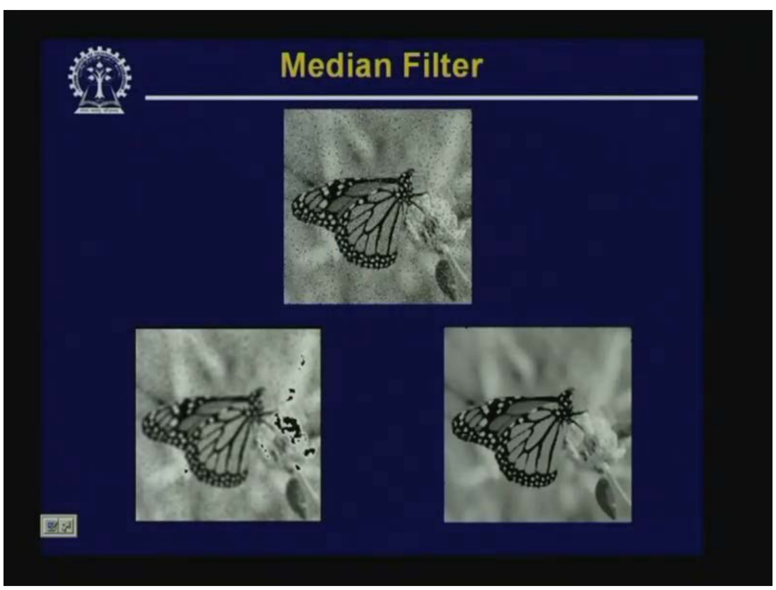
So here, we have shown one such result. On the top left is the original noisy image, on the top right is the image which is obtained using the box filter and the bottom image is the image which is obtained using the median filter and here it is quite obvious that when we go for the median filtering operation, the median filtering reduces the noise but at the same time, it maintains the sharpness of the image whereas, if we go for box filtering of higher dimension of higher size, then the noise is reduced but at the same time, the image sharpness is also reduced. That means the image gets blurred.

(Refer Slide Time: 6:42)



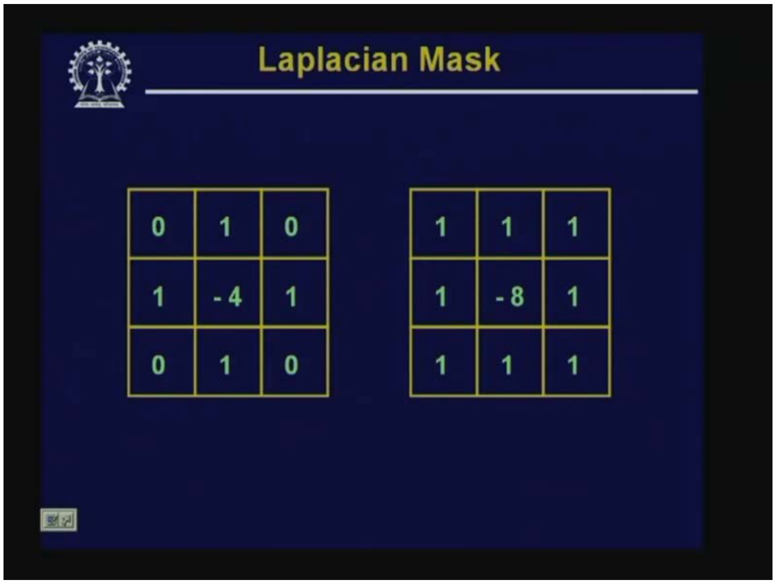
This is another set of results where you will find that if you compare the similar results that you have shown earlier using the median filter, the noise is almost removed but at the same time, the contrast of the image is also maintained. So, this is the advantage of the median filter that we get that in addition to removal of noise, you can maintain the contrast of the image. But this kind of median filtering, as we have mention that this is very suitable for a particular kind of noise, removal of a particular kind of noise which we have said the salt and pepper noise. The name comes because of the appearance of these noises in the given images.

(Refer Slide Time: 7:25)



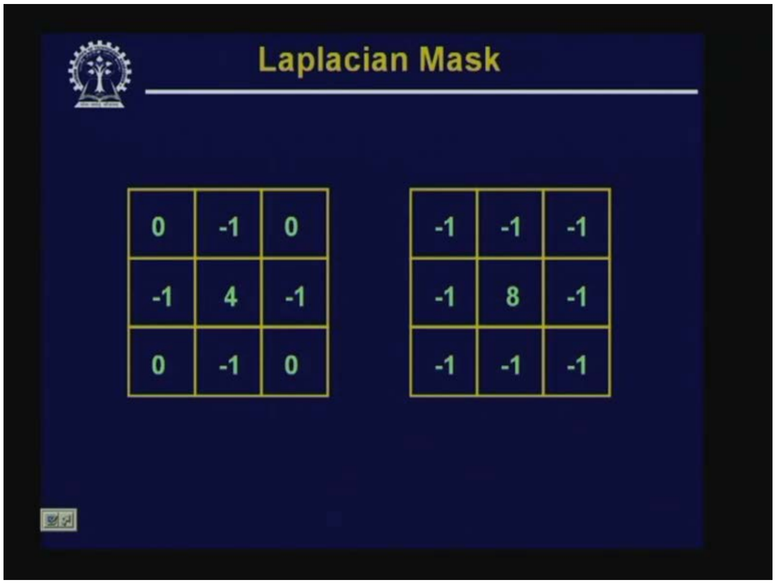
Then this shows another median filter output result. The bottom 2 images on the left side, it is the image obtained using the box filter on the right hand side, it is the image obtained using the median filter. The enhancement using the median filter over the box filter is quite obvious from this particular image.

(Refer Slide Time: 7:47)



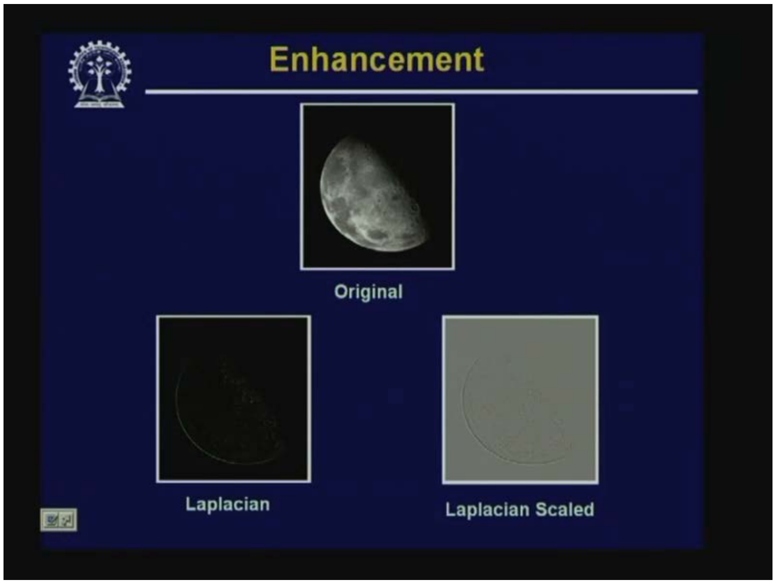
Then we then we have said that for enhancement operation, we use the second order derivatives and the kind of masks that we have used for the second order derivative is the Laplacian mask and for the Laplacian mask, these are the 2 different masks which we have used for Laplacian operation.

(Refer Slide Time: 8:07)



We can also use another type of masks where the center coefficients are positive. You find in case of earlier masks, the center coefficients are negative whereas, all the neighboring coefficients are positive in the Laplacian mask. In this case, the center coefficient is positive whereas, all other neighboring coefficients are negative.

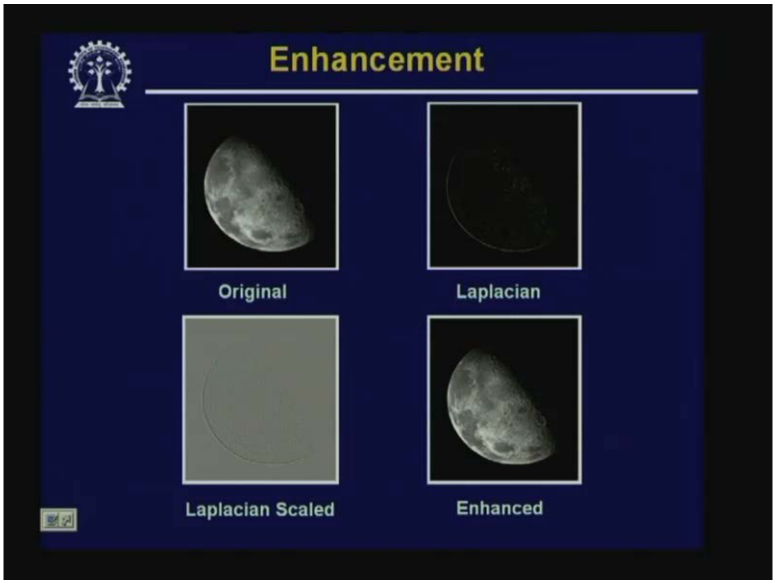
(Refer Slide Time: 8:27)



Now, using this Laplacian mask, we can find out the high frequency detailed contents of an image as has been shown in this particular one. Here you find that the original image, when it is processed using the Laplacian mask, the details of the image are obtained on the left hand side. Bottom left, we have shown the details of the image. On the bottom right what we have done is it is the same image which is displayed after scaling so that the details are displayed properly on the screen.

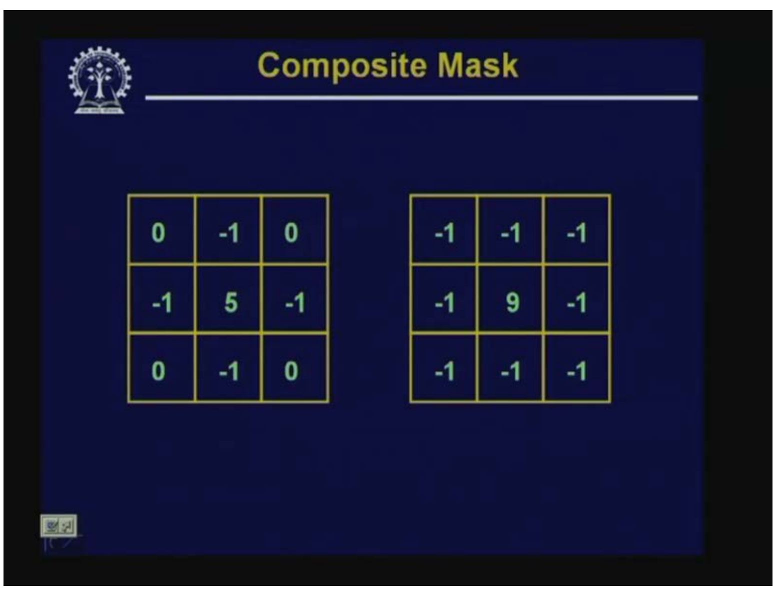
Now here, what has been done is we have just shown the details of the image. But in many applications what is needed is if this detailed information is super imposed on the original image, then it is better for visualization. So, these detailed images are to be added to the original image so that we can get an enhanced image.

(Refer Slide Time: 9:24)



So, the next one shows that if we have this original image, these are that same detailed images that we have shown earlier. On the right bottom, you have the enhanced image or the detailed images are added to the original image and for performing this operation, we can have a composite mask where the composite mask is given like this.

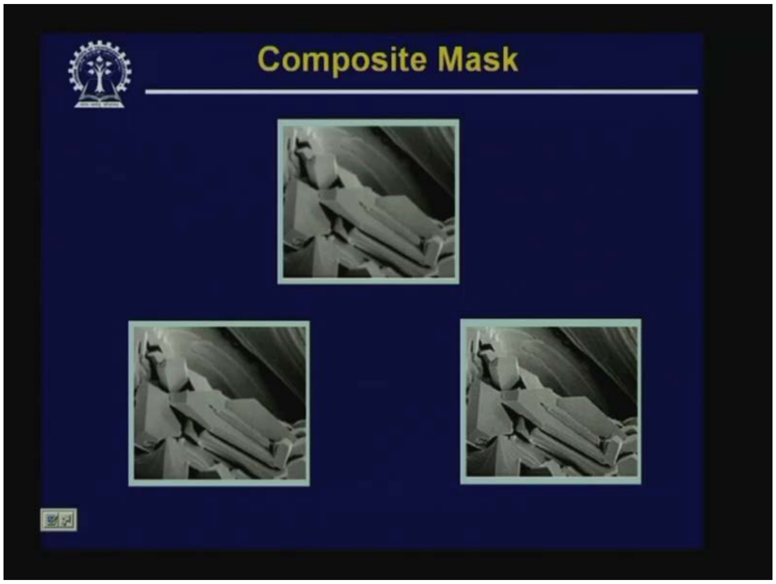
(Refer Slide Time: 9:38)



Here you find on the center pixel we have the center coefficient of the mask is equal to 5 whereas, you remember you recollect that in case of Laplacian mask, the center pixel of the corresponding mask was of equal to 4.

So, if I change from 4 to 5 that mean f (x, y) value, the original image is going to be added with the detailed image to give us the enhanced images. So, that is what is done by using this composite mask.

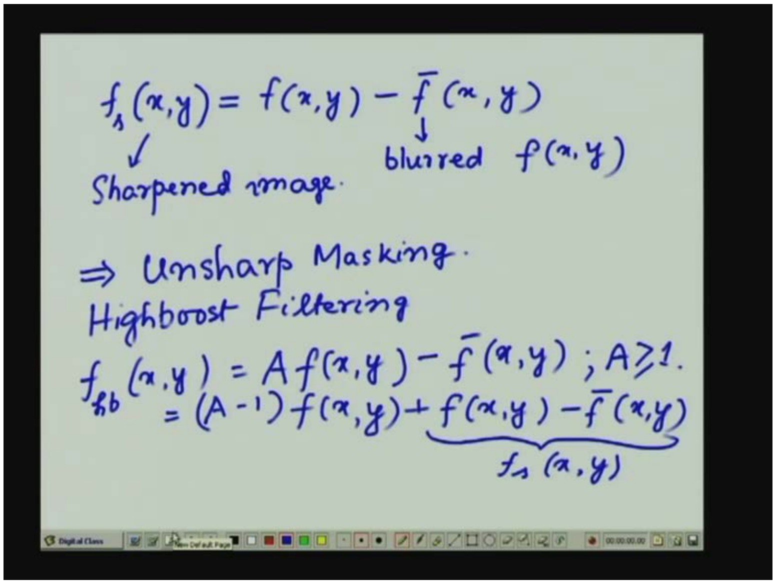
(Refer Slide Time: 10:11)



And, this is the result that we obtained using the composite mask similar to the one that we have shown earlier; you find that on the top, we have the original image and on the bottom right, we have the enhanced image. Bottom left is an enhanced image when we use a mask where only the horizontal and the vertical neighbors are non zero values whereas, the bottom right is obtained using the mask were we consider both the horizontal vertical and diagonal coefficients to be non zero values. And as it is quite clear from this particular result that when we go for this kind of mask having both horizontal, vertical and the diagonal components has non zero values, the enhancements is much more.

Now today, we will talk about some more spatial domain or mask operations. The first one that we will talk about is called an unsharp masking.

(Refer Slide Time: 11:11)



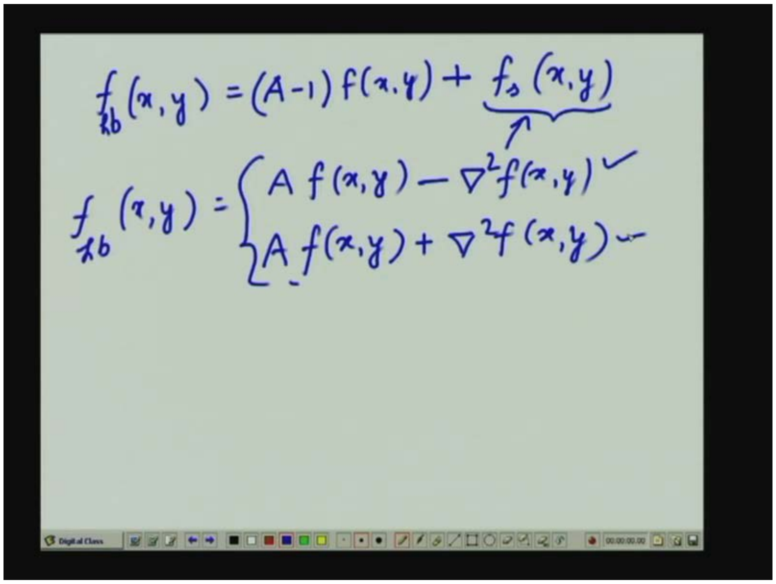
So, by unsharp masking, we mean; you know that for many years, in the publishing companies were using a kind of enhancement where the enhancement in the image was obtained subtracting a blurred version of the image from the original image. So, in such cases, the sharpened image was obtained as f_s (x, y) if I represent it by f_s as the sharpened image, then this was obtained by subtracting f (x, y) and f bar (x, y).

So, this f bar (x, y) is nothing but a blurred version or blurred f (x, y). So, if we subtract the blurred image from the original image what we get is the details in the image or we get a sharpened image. So, this f_s (x, y) is the sharpened image and this kind of operation was known as unsharped masking.

Now, we can slightly modify this particular equation to get an expression for another kind of masking operation which is known as high boost filtering. So, high boost filtering is nothing but a modification of this unsharp masking operation. So, we obtain high boost filtering as we can write it in this form f_{hb} (x, y) which is nothing but A times f (x, y) minus f bar (x, y) for A greater than or equal to 1.

So, we find that if I said the value of this constant A equal to 1, then this high boost filtering becomes same as unsharp masking. Now, you I can rewrite this particular expression, I can rewrite this in the form (A minus 1) f (x, y) plus f (x, y) minus f bar (x, y). Now, this f (x, y) minus f bar (x, y), this is nothing but the sharpened image f_s (x, y).

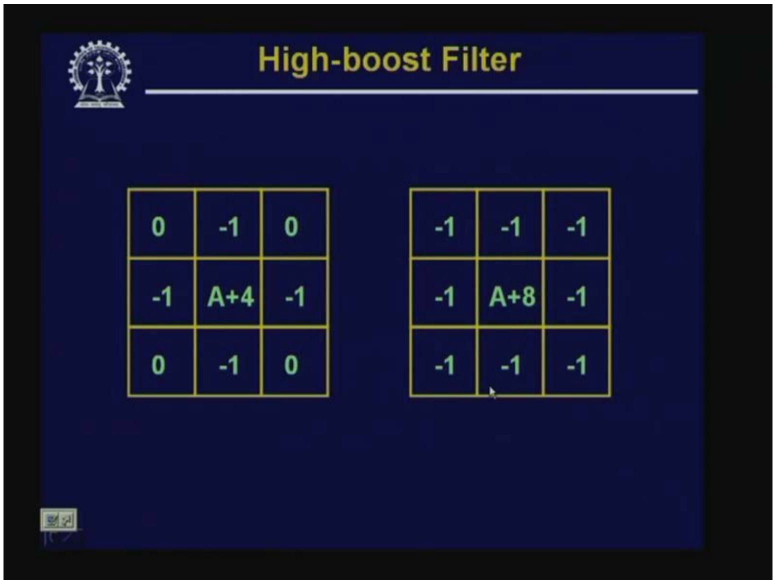
(Refer Slide Time: 14:17)



So, the expression that I finally get for high boost filtering is f_{hb} (x, y) is equal to A minus 1 f (x, y) plus f_s (x, y). Now, it does not matter in which way we obtain the sharpened images. So, if I use the Laplacian operator to obtain this sharpened image; in that case, the high boost filtered output f_{hb} (x, y) simply becomes A f (x, y) minus the Laplacian operator on f (x, y) and this is the case when the center coefficient in the Laplacian mask will be negative or I will have the same expression which is written in the form A f (x, y) plus Laplacian of f (x, y) when the center coefficient in the Laplacian mask is equal to positive.

So, as we have seen earlier that this first expression will be used if the center coefficient in the Laplacian mask is negative and the second expression will be used if the center coefficient in the center coefficient in the Laplacian mask is positive.

(Refer Slide Time: 15:51)

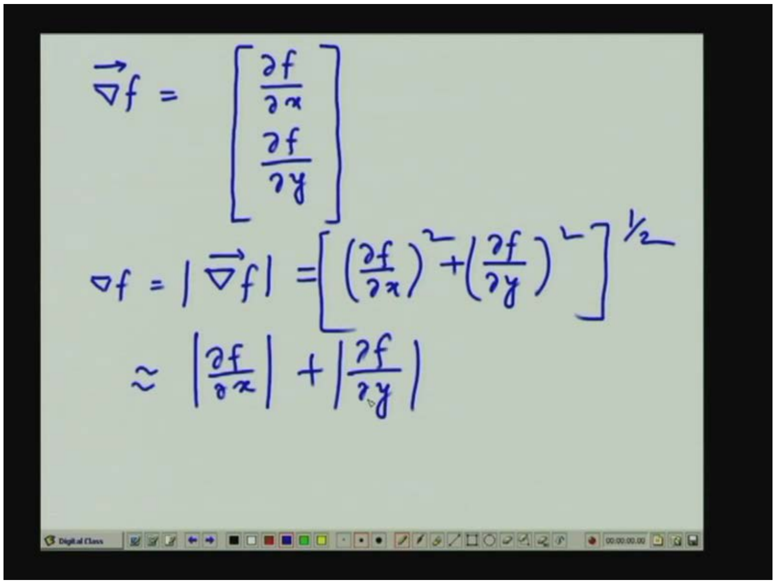


So, using this we can get a similar type of mask where the mask is given by this particular expression. So, using these masks, we can go for high boost filtering operation and if I use this high boost filtering, I get the high boost output as we have already seen earlier.

Now, so far the kinds of derivative operators that we have used for sharpening operation, all of them are second order derivative operators; we have not used first order derivative operators for filtering so far but first order derivative operators are also capable of enhancing the content of the image particularly at discontinuities and at region boundaries or edges.

Now, the way we obtain the first order derivative of a particular image is like this.

(Refer Slide Time: 16:53)

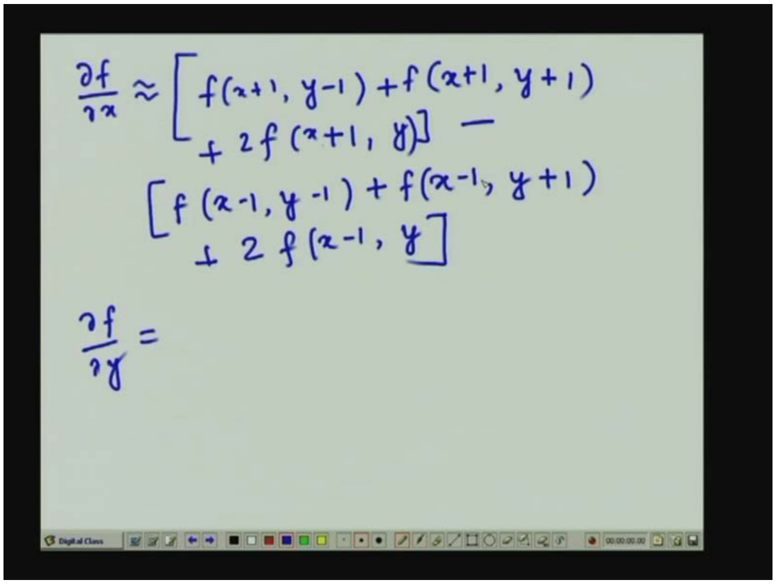


What you used for obtaining the first order derivatives is by using the gradient operator where the gradient operator is given like this. Gradient of a function f as the gradient is a vector, so we will write as a vector is nothing but dell f dell x and dell f dell y. So, this is what gives the gradient of a function f and what we are concerned about for enhancement is the magnitude of the gradient.

So, magnitude of the gradient, we will write it as dell f which is nothing but magnitude of the vector grade f which is usually dell f by dell x square plus dell f by dell y square and square root of this. But you find that this particular expression if I use, this leads to some computational difficulty in the sense that we have go for squaring and then square root and getting an square root in the digital domain is not an not an easy task.

So, what we do is we go for an approximation of this and the approximation is obtained as dell f dell x magnitude plus dell f dell y magnitude of this. So, this is what gives us the first order derivative operator on an image.

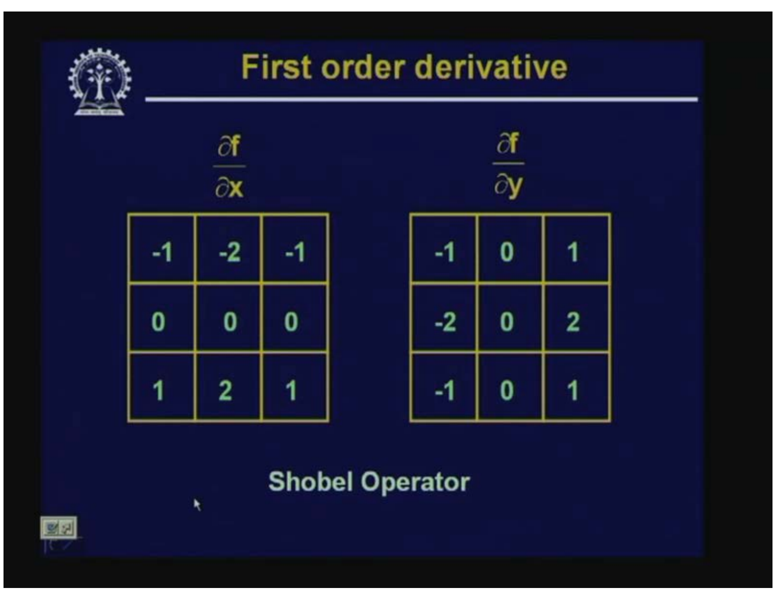
(Refer Slide Time: 18:35)



And, if I want to obtain dell f dell x, you find that this dell f dell x can simply be computed as f (x plus 1, y minus 1) plus f (x plus 1, y plus 1) plus 2 f (x plus 1, y) minus f (x minus 1, y minus 1) plus f (x minus 1, y plus 1) plus 2 f (x minus 1, y). So, this is the first order derivative along x direction and in the same manner, we can also obtain the first order derivative in the y direction.

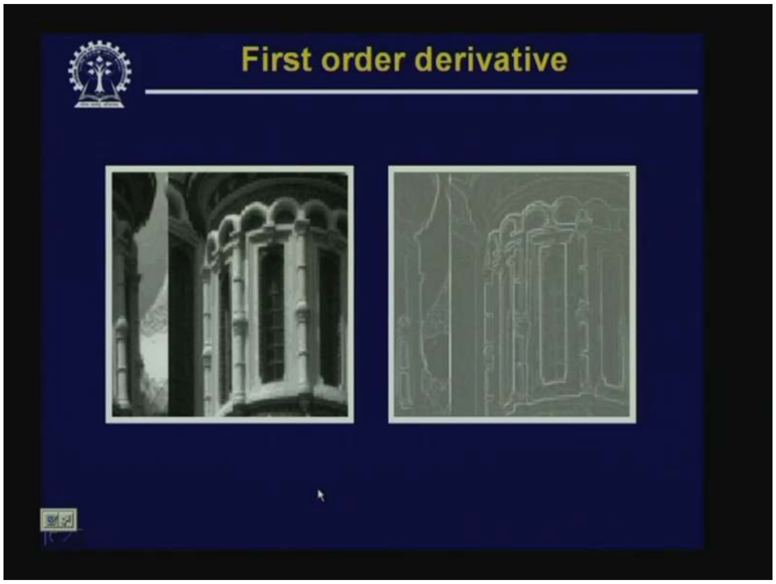
Now, once we have this kind of discrete formulation of the first order derivative; so similarly, I can find out dell f dell y which also which will also have a similar form. So, once I have such discrete formulations of the first order derivatives, we can have a mask which will compute the first order derivative of an image.

(Refer Slide Time: 20:12)



So, for computing the first order derivative along x direction, the left hand side shows the mask and for computing the first order derivative along y direction, the right hand side shows the mask. And later on, we will see that these operators are known as Shobel operator and using these first order derivatives; when we apply these first order derivatives on the images, the kind of processed image that we get is like this.

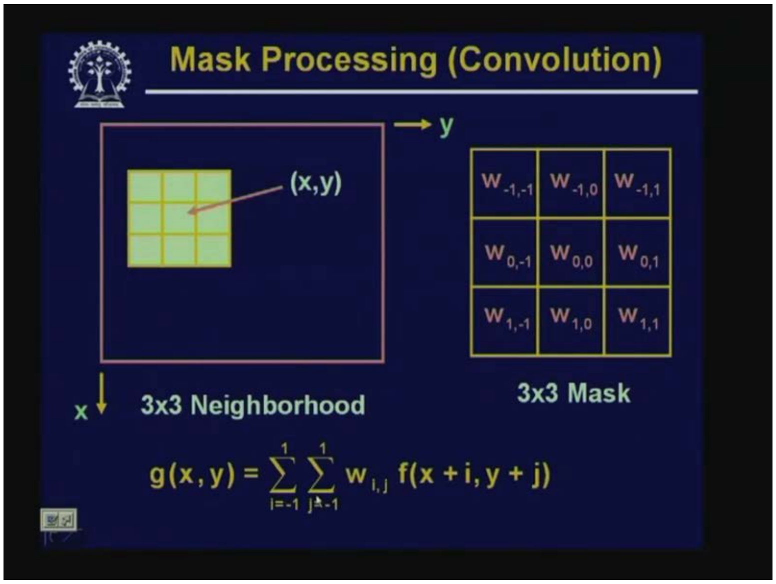
(Refer Slide Time: 20:42)



So, you find that on the left hand side, we have the original image and on the right hand side, we have the processed image and in this case, you find that this processed image region image which highlights the edge regions or discontinuity regions in the original image. Now, in many practical applications such simple derivative operators are not sufficient. So in such cases, what we may have to do is we may have to go for combinations of various types of operators which give us the enhanced image. So, with this we come to the end of our discussion on spatial domain processing techniques.

Now, we start discussion on the frequency domain processing techniques. Now, so far you must have noticed that this mask operations or the spatial domain operations using the masks, whatever we have done that is nothing but convolution operation in 2 dimension.

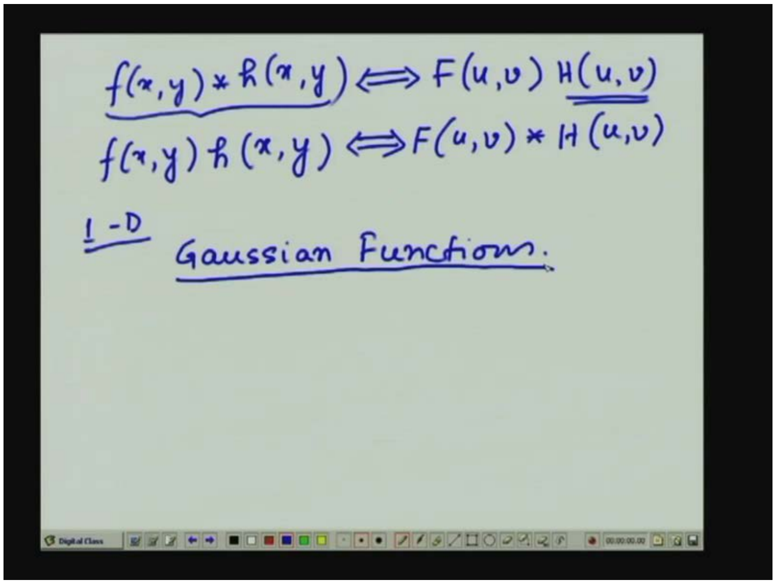
(Refer Slide Time: 21:58)



So what we have done is we have the original image f (x, y), we defined a mask corresponding to the type of operation that we want to perform on the original image f (x, y) and using this mask the kind of operation that is done the mathematical expression of this is given on the bottom and if you analyze this, you will find that this is nothing but a convolution operation.

So, using this convolution operation, we are going for spatial domain processing of the images. Now, we have seen we have already seen during our earlier discussions that a convolution operation in the spatial domain is equivalent to multiplication in the frequency domain. Convolution in the spatial domain is equivalent to multiplication in the frequency domain. Similarly, a convolution in the frequency domain is equivalent to multiplication in the spatial domain.

(Refer Slide Time: 23:05)



So, what we have seen is that if we have a convolution of say 2 functions f (x, y) and h (x, y) in the spatial domain, the corresponding operation in the frequency domain is multiplication of F (u, v) and H (u, v) where F (u, v) is the Fourier transform of this spatial domain function f (x, y) and h (u, v) is the Fourier transform of the spatial domain function h (x, y).

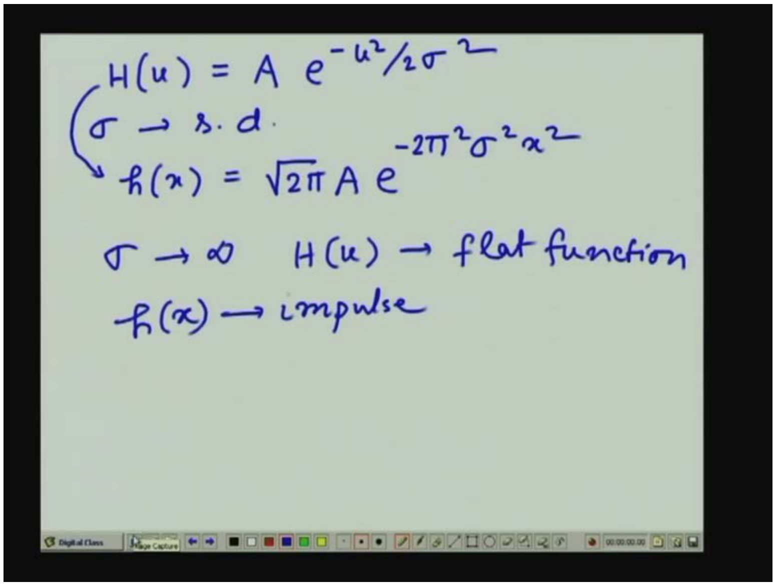
Similarly, if we multiply two functions f (x, y) and h (x, y) in the spatial domain, the corresponding operation in the frequency domain is the convolution operation of the Fourier transforms of f (x, y) which is F (u, v) that has to be confirmed with H (u, v). So, these are the convolution theorems that we have done during our previous discussions.

So, to perform this convolution operation; the equivalent operation can also be done in the frequency domain if I take the Fourier transform of the image f (x, y) and I take the Fourier transform of the spatial mask that is h (x, y). So, the Fourier transform of the spatial mask h (x, y) as we have said that this is nothing but H (u, v) in this particular case.

So, the equivalent filtering operations, we can do in the frequency domain by choosing the proper filter H (u, v). Then after taking the product of F (u, v) and H (u, v) if I take the inverse Fourier transform, then I will get the processed image in the spatial one. Now, to analyze this further, what we will do is we will take the case in 1 dimensional and we will consider the filters based on Gaussian functions for analysis purpose.

The reasons we are choosing this filters based on Gaussian functions is that the shapes of such functions can be easily specified and easily analyzed. Not only that; the forward transformation, the forward Fourier transformation and the inverse Fourier transformation of Gaussian functions are also Gaussian.

(Refer Slide Time: 25:48)



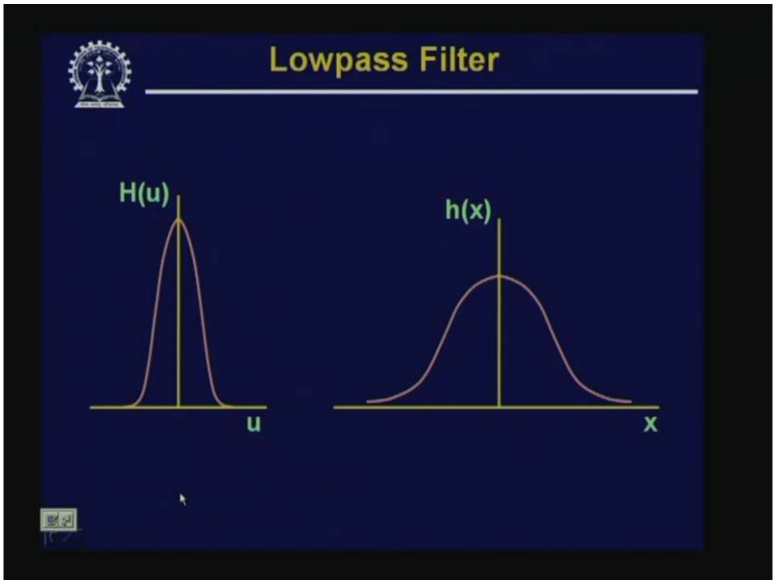
So, if I take a Gaussian filter in the frequency domain; I will write a Gaussian filter in the frequency domain as H (u) is equal to some constant to A e to the power minus u square by 2 sigma square where sigma is the standard deviation of the Gaussian functions and if I take the inverse Fourier transform of this, then the corresponding filter in the spatial domain will be given by h (x) is equal to root over 2 pie A e to the power minus 2 pie square sigma square x square.

Now, if you analyze these 2 functions that is H (u) in the frequency domain and h (x) in the spatial domain, you find that both these functions are Gaussian as well as real and not only that; both this functions, they behave reciprocally with each other. That means when H (u) has a broad profile; this particular function H (u) in the frequency domain, it has a broad profile that is it has a large value of standard deviation sigma. The corresponding h x in the spatial domain will have a narrow profile.

Similarly, if H (u) has narrow profile, h (x) will have a broad profile. Particularly, when this sigma tends to infinity, then this function H (u) this tends to be a flat function and in such case, the corresponding spatial domain filter h (x) this tends to be an impulse function. So, this shows that both H (u) and h (x), they are reciprocal to each other.

Now, let us see what will be the nature of these functions, nature of such low pass filter functions.

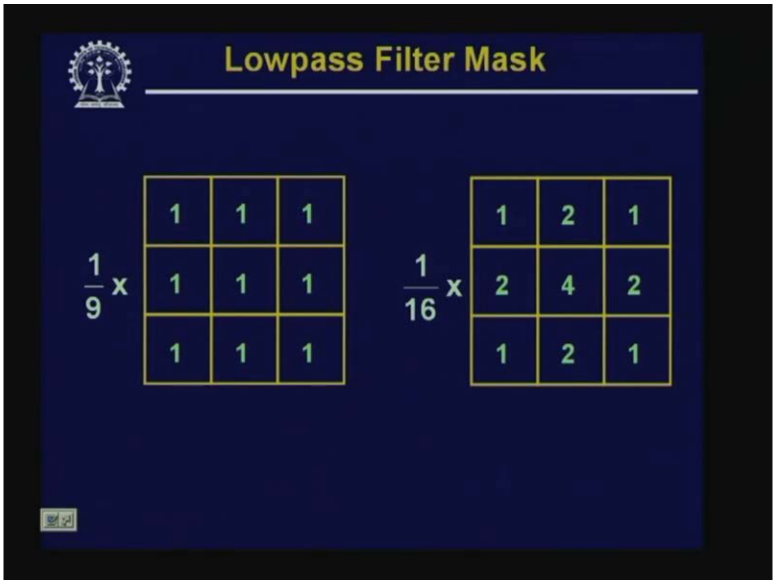
(Refer Slide Time: 28:07)



So here, on the left hand side, we have shown the frequency domain filter H (u) as a function of u and on the right hand side, we have shown the corresponding spatial domain filter h (x) which is a function of x. Now from these filters, it is quite obvious that all the values once I specify a filter H (u) as a function of u in the frequency domain, the corresponding filter h (x) in the spatial domain, they will have all positive values.

That is none h (x) never become positive negative for any value of x and the narrowed the frequency domain filter, more it will attenuate the low pass frequency components resulting in more blurring effect. And if I say make the frequency domain filter narrower that means the corresponding spatial domain filter or spatial domain mask will be flatter. That means the mask size in the spatial domain will be larger.

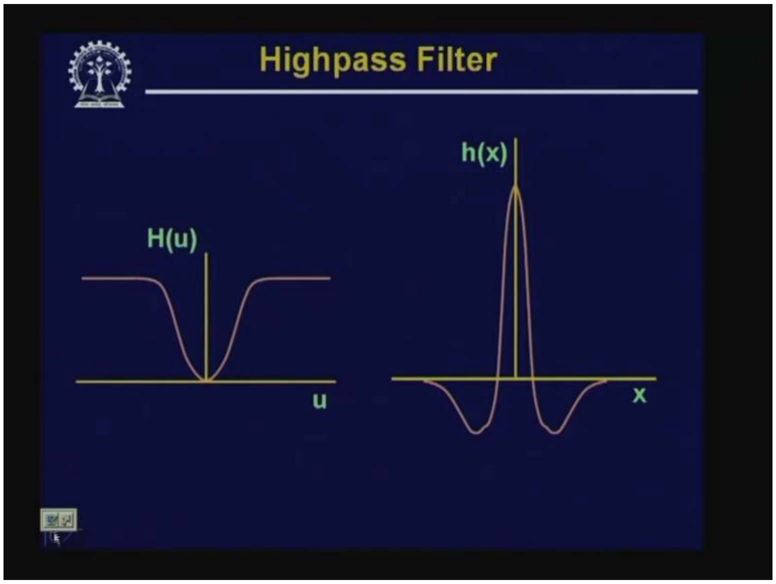
(Refer Slide Time: 29:22)



So, this slide shows 2 such masks that we have already discussed during our previous discussion. So, this is the mask where all the coefficients are positive and same and in this mask, the coefficients are all positive but the variation shows that it is having some sort of Gaussian distribution in nature and we have already said that if the frequency domain filter becomes very narrow, it will attenuate even the low frequency components leading to a blurring effect of the processed image.

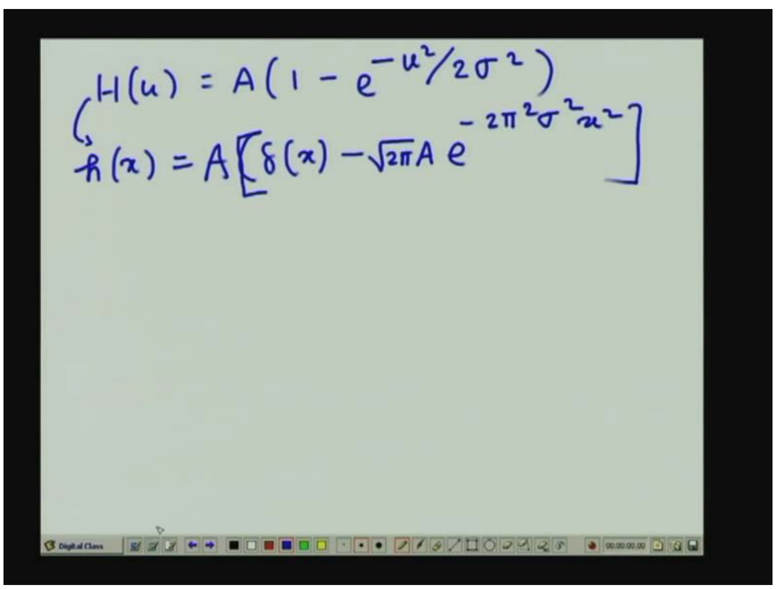
Correspondingly in the high pass correspondingly in the spatial domain, the mask size will be larger and you have seen through our results that if I use a larger mask size for smoothing operation, then the image gets more and more blurred.

(Refer Slide Time: 30:28)



Now, in the same manner, as we have said the low pass filter; we can also make the high pass filters again in the Gaussian domain.

(Refer Slide Time: 30:38)

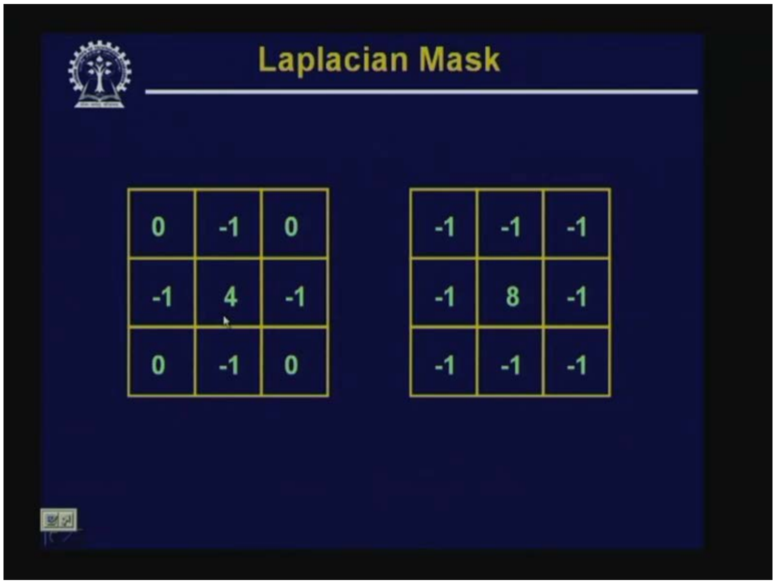


So in this case, in case of Gaussian domain, using the Gaussian function, the high pass filter H (u) can be defined as A into 1 minus e to the power minus u square by 2 sigma square. So, this is the high pass filter which is defined using the Gaussian function. If I take the inverse Fourier transform of this, the corresponding spatial domain filter will be given by h (x) equal to A into delta x minus the same square root of 2 pie into A into e to the power minus 2 pie square sigma square x square.

So, if I plot this in the frequency domain, this shows the high pass filter in the frequency domain. So, as it is quite obvious from this plot that it will attenuate the low frequency components whereas it will pass the high frequency components and the corresponding filter in the spatial domain is having this form which is given by h (x) as the function of x.

Now, as you note from this particular figure, from this particular function h (x) that h (x) can assume both positive as well as negative arrows and an important point to note over here is once h (x) becomes negative; it will remain negative, it does not become positive anymore and in the spatial domain, the Laplacian operator that we have used earlier, the Laplacian operator was of similar nature.

(Refer Slide Time: 32:33)

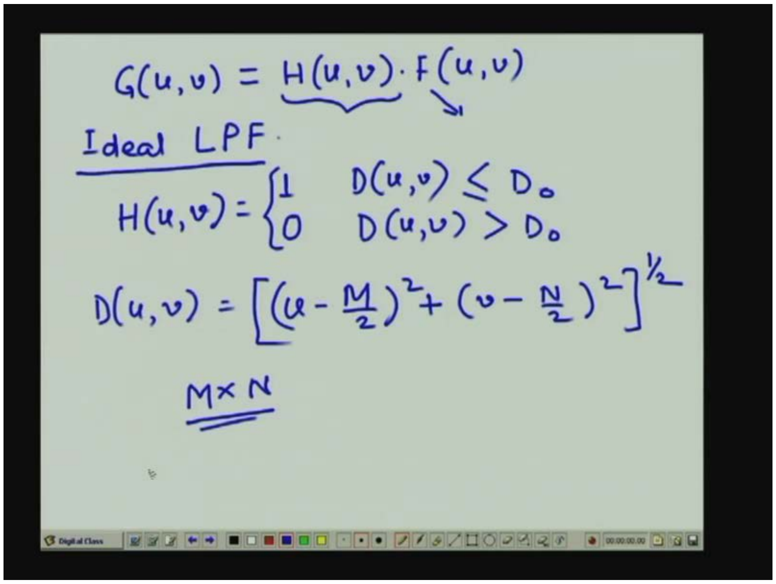


So, the Laplacian mask that we have used, we have seen that the center pixel is having a positive value whereas all the neighboring pixels have the negative values and this is true for both the Laplacian masks if I consider only the vertical and horizontal components or whether along with vertical and horizontal components, I also consider the diagonal components.

So, these are the 2 Laplacian masks where the center coefficient is positive and the neighboring coefficients once they become negative, they will remain negative. So, this shows that using the Laplacian mask in the spatial domain, the kind of operation that we have done is basically a high pass filtering operation.

So, now first of all, we will consider the smoothing frequency domain filters or low pass filters in the frequency domain. Now, as we have already discussed that edges as well as sharp transitions like noises, they lead to high frequency components in the image and if we want to reduce these high frequency components, then the kind of filter that we have to use is a low pass filter where the low pass filter will allow the low frequency components of the input image to be passed to the output and it will cut off the high frequency components of the input image which will not be passed to the output.

(Refer Slide Time: 34:09)



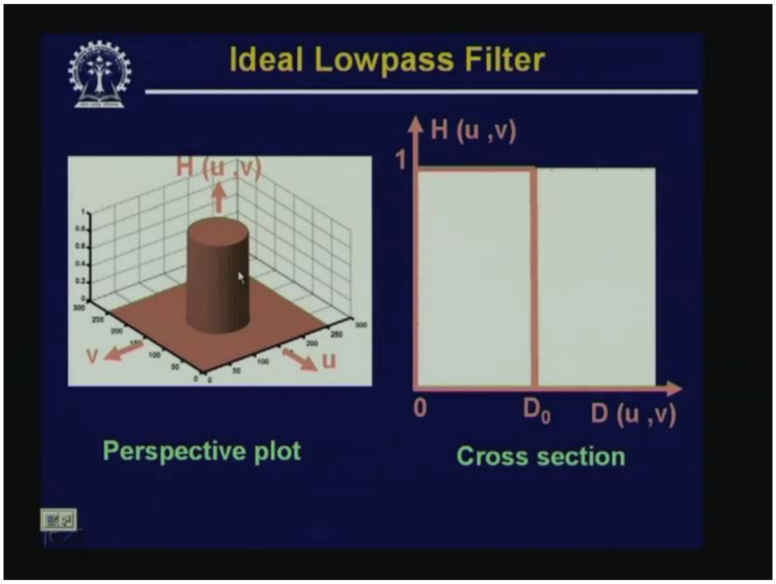
So, our basic model for this filtering operation will be like this that we will have the output in the frequency domain which is given by G (u, v) which is equal to H (u, v) multiplied by F (u, v) where this F (u, v) is the Fourier transform of the input image and we have to select a proper filter function H (u, v) which will attenuate the high frequency components and it will let the low frequency components to be passed to the output.

Now here, we will consider an ideal low pass filter where we will assume the ideal low pass filter to be like this that H (u, v) is equal to 1 if D (u, v) where D (u, v) is the distance of the point (u, v) in the frequency domain from the origin of the frequency rectangle. So, if D (u, v) is less than or equal to some value say D_0, then H (u, v) H (u, v) will be equal to 1 and this will be equal to 0 if the distance from the origin of the point uv is greater than D_0.

So, this clearly means that if I multiply F (u, v) with such an H (u, v), then all the frequency components laying within a circle of radius D_0 will be passed to the output and all the frequency components laying outside this circle of radius D_0 will not be allowed to be passed to the output.

Now, if the Fourier transform F (u, v) is centered is the centered Fourier transform that means the origin of the Fourier transform rectangle is set at the middle of the rectangle; then this D (u, v), the distance value is simply computed as u minus M by 2 square plus v minus N by 2 square, square root of this where we are assuming that we have an image of size M by N. So, for an M by N image size, D (u, v) will be computed like this if the Fourier transform F (u, v) is the centered Fourier transformation.

(Refer Slide Time: 36:56)

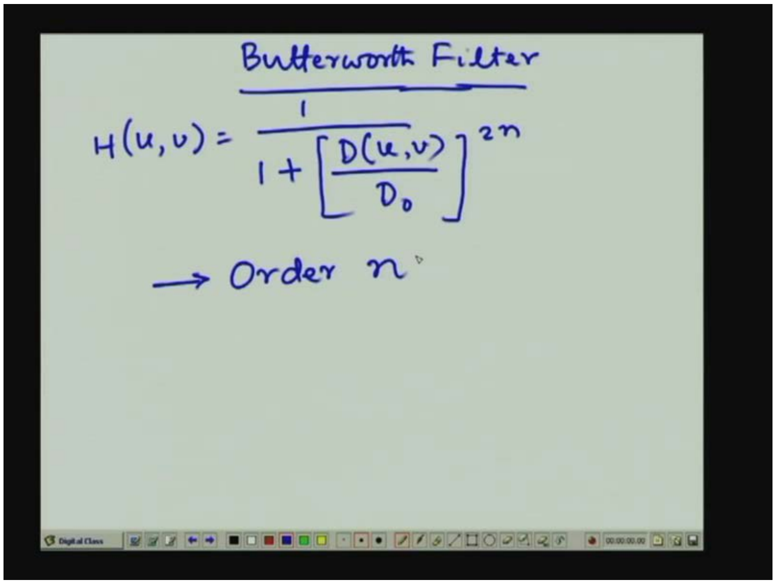


A plot of this kind of function is like this. So, here you find that the left hand side shows the perspective plot of such an ideal filter whereas on the right hand side, we just show the cross section of such an ideal filter and in such cases, we define a cut off frequency of the filter to be the point of transition between H (u, v) equal to 1 and H (u, v) equal to 0.

So, in this particular case, this point of transition is the value D_0, so you consider D_0 to be the cut off frequency of this particular filter. Now, it may be noted that such a sharp cut off filter is not realizable using the electronic components. However, using software using computer program it is different because we are just letting some values to be passed to the output and we are making the other values to be 0.

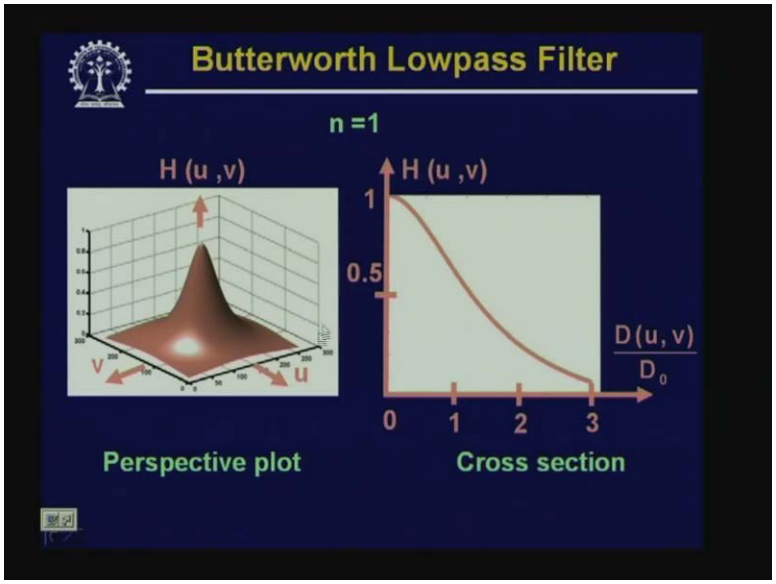
So, this kind of ideal low pass filter can be implemented using software whereas using electronic components, we may not be or we are not able to implement such ideal low pass filters. So, a better approximation of this is a filter which is called butter worth filter.

(Refer Slide Time: 38:10)



So, a butter worth filter, a butter worth low pass filter is the response, the frequency response of this is given by H (u, v) is equal to 1 upon 1 plus D (u, v) by D_0 to the power 2n. So, this is butter worth filter of order n. The response of or the plot of such a butter worth filter is shown here.

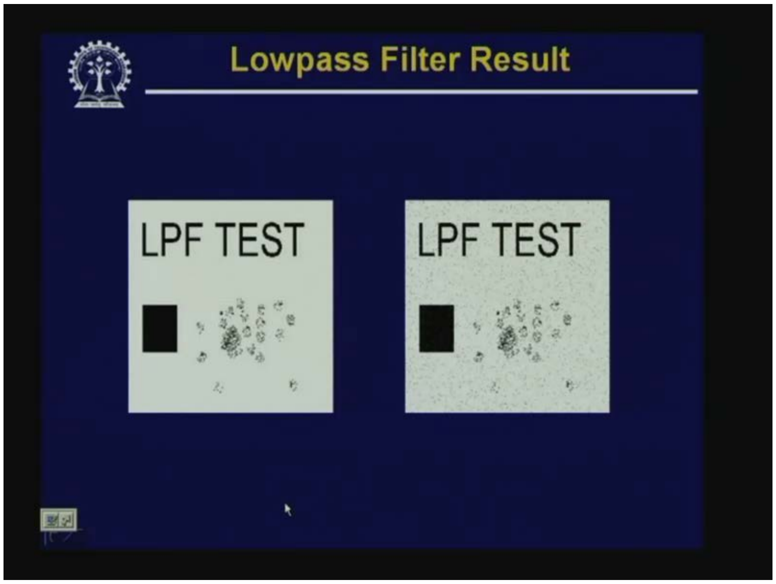
(Refer Slide Time: 39:13)



So here, we have shown the butter worth butter worth filter, the perspective plot of the butter worth filter and on the right hand side, we have shown the cross section of this butter worth filter. Now, if I apply the ideal low pass filter and the butter worth filter on an image, let us see what will be the kind of the output image that we will get.

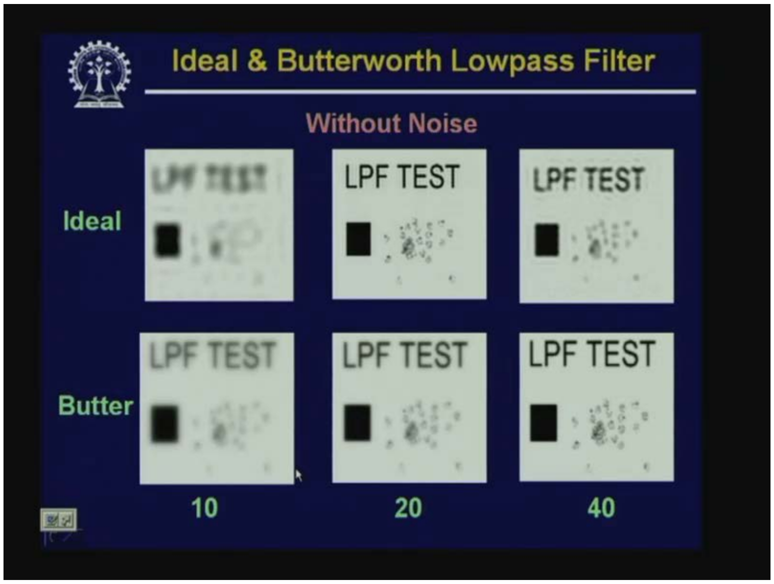
So, in all this cases, we assume that first we take the Fourier transform of the image, then multiply that Fourier transformation with the frequency response of the filters, then whatever the product that we get, we take the inverse Fourier transformation of this to obtain our processed image in the spatial domain.

(Refer Slide Time: 40:01)



So here, we use 2 images for test purpose. On the left hand side, we have shown an image without any noise and on the right hand side, we have shown an image where we have added some amount of noise.

(Refer Slide Time: 40:15)

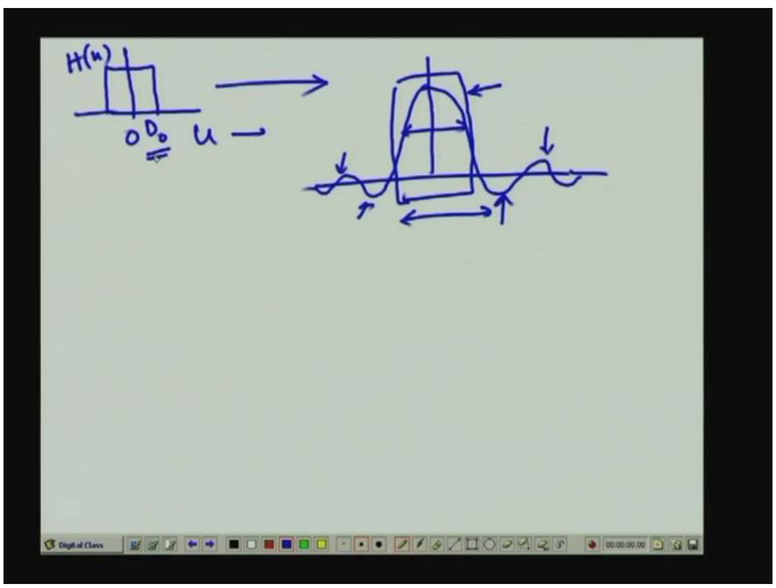


Then, if I process that image using the ideal low pass filter and using the butter worth filter; the top rows shows the results with ideal low pass filter when the image is without noise and the bottom row shows the result by applying the butter worth filter again when there is no noise contamination with the image.

Here, you find as the top row shows that if I use the ideal low pass filter for the same cutoff frequency say 10, the blurring of the image is very high compared to the blurring which is introduced by the butter worth filter. If I increase the cut off frequency, when I go for cut off frequency of 20; in that case you find that in the original image, in the ideal low pass filtered image the image is very sharp but the disadvantage is that if you simply look at this locations say along this locations, you find that there is some ringing effect. That means there are a number of lines, undesired lines which are not present in the original image.

Same is the case over here. So, the butter worth filter, butter worth low pass filter; it introduces the ringing effect, the ringing effect which are not visible in case of butter worth filter.

(Refer Slide Time: 42:00)

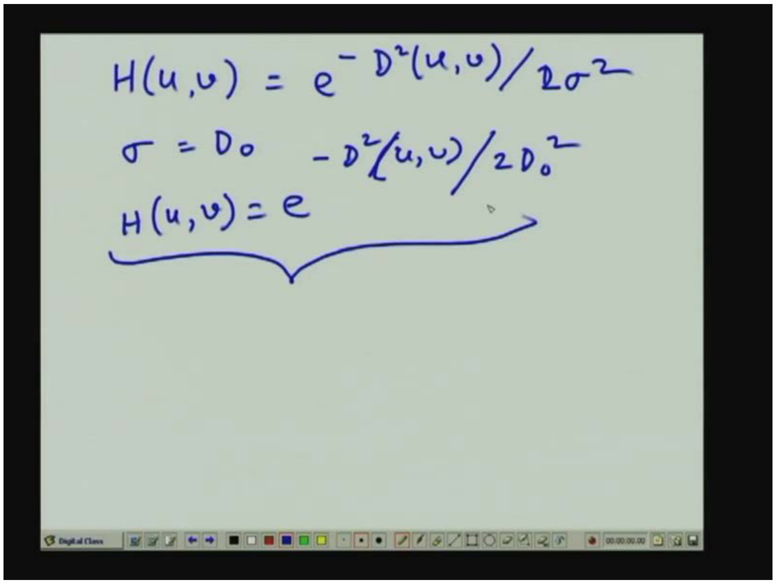


Now, the reason why the ideal low pass filters introduces the ringing effect is that we have seen that for an ideal low pass filter in the frequency domain, the ideal low pass filter response was something like this. So, if I plot u verses H (u), this was the response of the ideal low pass filter. Now, if I take the inverse Fourier transform of this, corresponding h (x) will have a function of this form, like this. So here, you find that there is a main component which is the central component and there are other secondary components.

Now, the spread of this main component is inversely proportional to D_0 which is the cut off frequency of the butter of the ideal filter, ideal low pass filter. So, as I reduce D_0, this spread is going to increase and that is what is responsible for more and more blurring effect of the smoothed image. Whereas, all the secondary components; the number of this components again over an unit length is again an inverse function, inversely proportional to this cut off frequency D_0 and these are the once which are responsible for ringing effect.

When I use butter worth filter, the outputs that we have shown here using the butter worth filters, these outputs are obtained using butter worth filter of order 1 that is value of N is equal to 1. So, butter worth filter of order 1 does not leads to any kind of ringing effect. Whereas, if I go for butter worth filter of higher order that may lead to the ringing effect. In the same manner, we can also go for Gaussian low pass filter.

(Refer Slide Time: 44:01)

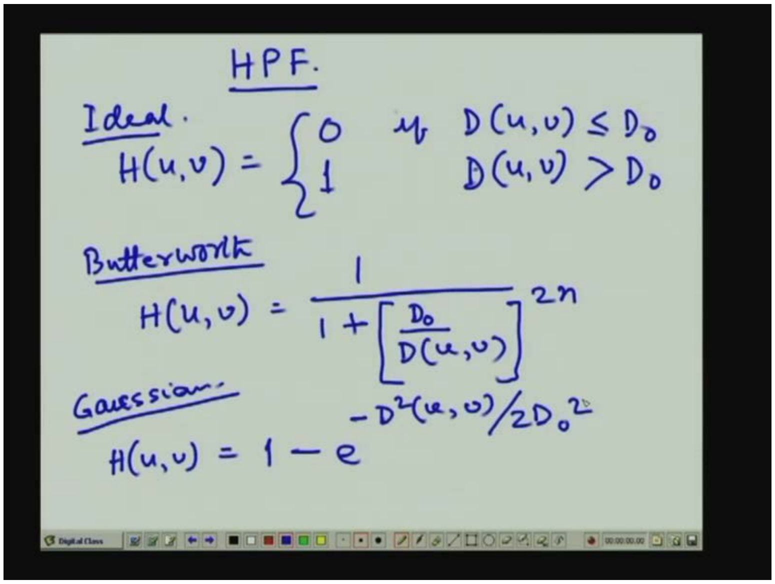


And we have already said that for a Gaussian low pass filter, the filter response H (u, v) is given by e to the power minus D square (u, v) upon 2 sigma square and if I allow sigma to be equal to the cut off frequency say D_0, then this H (u, v) the filter response will be e to the power minus D square uv upon 2 D_0 square.

Now, if I use such a Gaussian low pass filter for filtering operation and as we have already said the inverse Fourier transform of this is also Gaussian in nature; so using the Gaussian filters, we will never have any ringing effect in the processed image. So, this is the kind of the low pass filtering operation or smoothing operations in the spatial domain that we can have. We can also have the high frequency operation or sharpening filters in the frequency domain.

So, as low pass filters give the smoothing effect, the sharpening effect is given by the high pass filter. Again, we can have the ideal high pass filter, we can have the butter worth high pass filter, we can also have the Gaussian high pass filter.

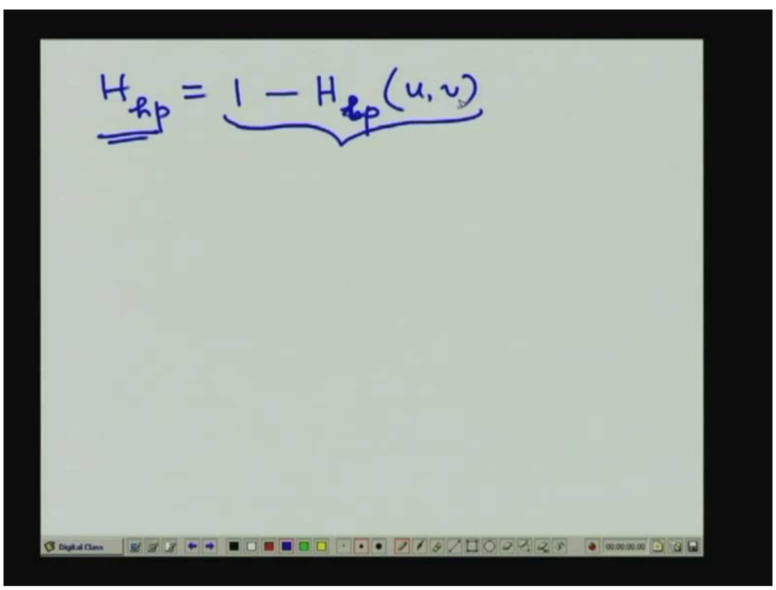
(Refer Slide Time: 45:31)



So, just in the reverse way we can define an ideal high pass filter as, for an high pass filter, the ideal high pass filter will be simply H (u, v) is equal to 0 if D (u, v) is less than or equal to D_0 and this will be equal to 1 if D (u, v) is greater than D_0. So, this is the ideal high pass filter.

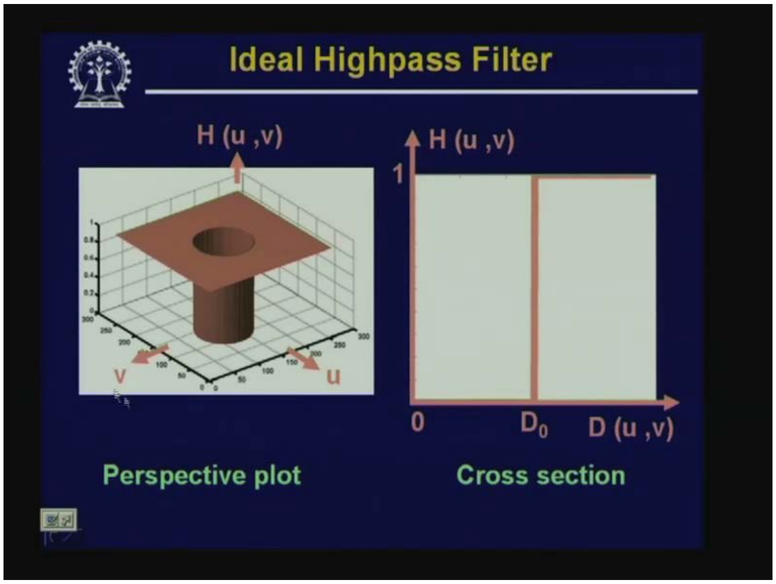
Similarly, we can have butter worth high pass filter where H (u, v) will be given by the expression 1 upon 1 plus D_0 by D (u, v) to the power 2n and we can also have the Gaussian high pass filter which is given by H (u, v) is equal to 1 minus e to the power minus D square (u, v) upon 2 D_0 square and you find that in all these cases; the response, the frequency response of an high pass filter if I write it as H_{hp} is nothing but 1 minus the response of a low pass filter.

(Refer Slide Time: 46:56)



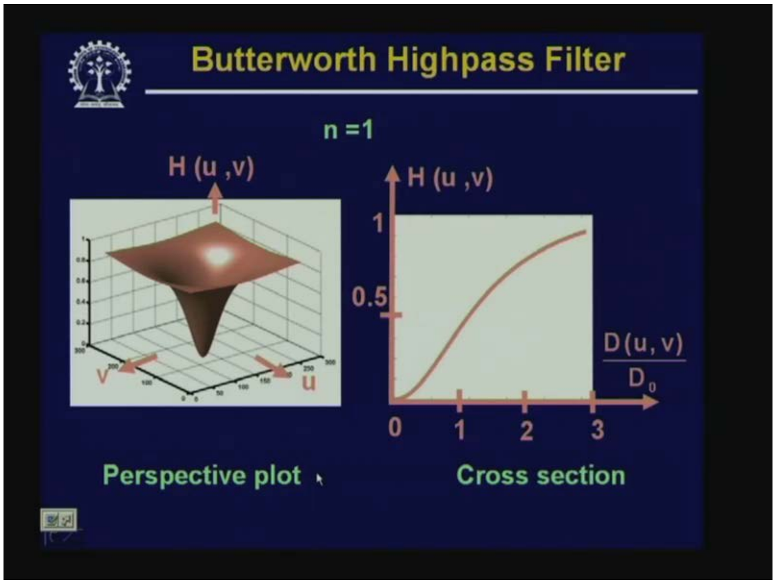
So, the high pass filter response can be obtained by the low pass filter response where the cutoff frequencies are same. Now, using such high pass filters, the kind of results that we can obtain is given here.

(Refer Slide Time: 47:30)



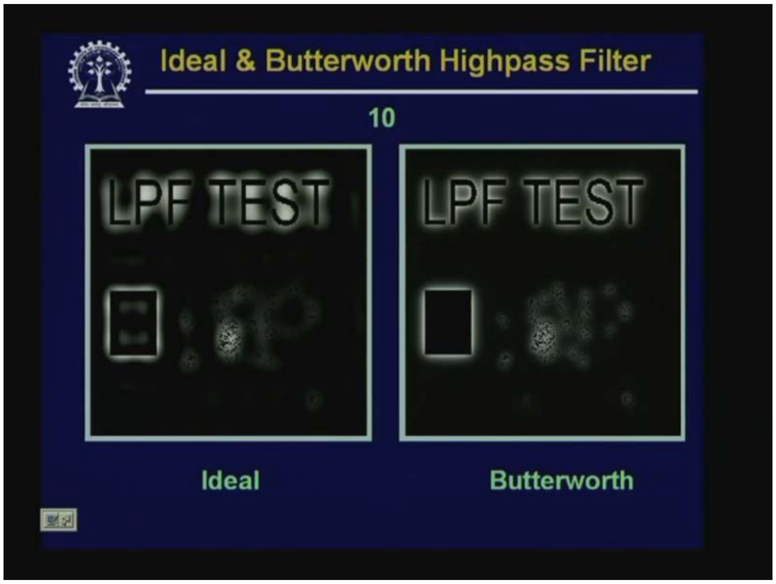
So, this is the ideal high pass filter response where the left hand side gives you the perspective plot and the right hand side gives you the cross section.

(Refer Slide Time: 47:43)



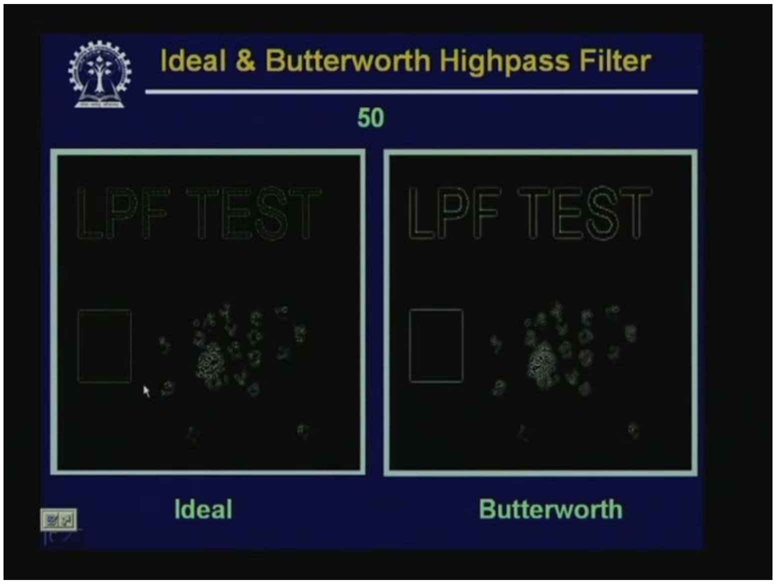
This shows the butter worth filter perspective plot as well as cross section of butter worth filter of order 1 and if I apply such high pass filters to the image to the same image, then the result that will obtained is something like this.

(Refer Slide Time: 47:57)



So here, on the left hand side, this is the response of an ideal high pass filter. On the right hand, side you have shown the response of butter worth high pass filter and in both these cases, the cut off frequency was taken to be equal to 10.

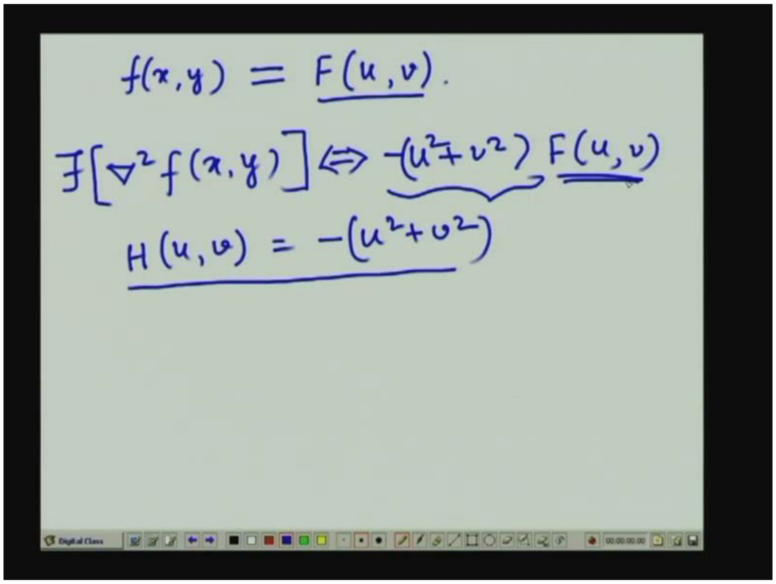
(Refer Slide Time: 48:20)



This one where the cutoff of frequency was taken to be equal to 50 and if you closely look at the ideal filter output; here again you find that you can obtain, you can find that there are ringing effects around this boundaries whereas in case of butter worth filter, there is no ringing effect. And again, we said that this is the butter worth filter of order 1 if I go for higher order butter worth filters that also may lead to ringing effects whereas if I go for a high pass filter which is Gaussian high pass filter, the Gaussian high pass filter does not leads to any ringing effect.

So, using this high pass filters, I can go for smoothing operation using the low pass filters, I can go for the smoothing operation and using the high pass filters, I can go for image sharpening operation. The same operation can also be done using the Laplacian in the frequency domain.

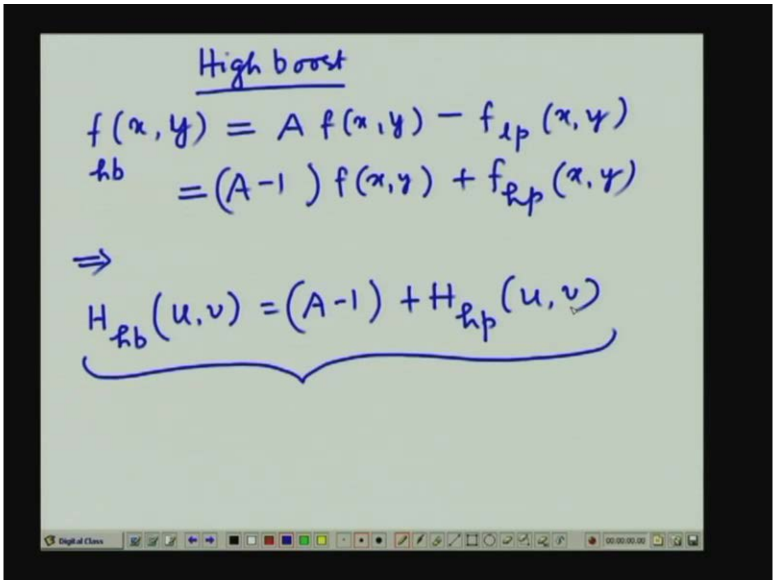
(Refer Slide Time: 49:32)



It is simply because if I take the Laplacian of a function; if for a function f (x, y), I get the corresponding frequency domain say F (u, v) the corresponding Fourier transform, then the Laplacian operator if I perform del square f (x, y) and take the Fourier transform of this, this will be nothing but it can be shown it will be equal to minus u square plus v square into F (u, v).

So using this operation, if I consider say H (u, v) is equal to minus u square plus v square and using this as a filter, I filter this F (u, v) and after that I compute the inverse Fourier transformation; then the output that we get is nothing but a Laplacian operated output which will be obviously an enhanced output. Another kind of filtering that we have already done during in connection with our spatial domain operation that is high boost filtering.

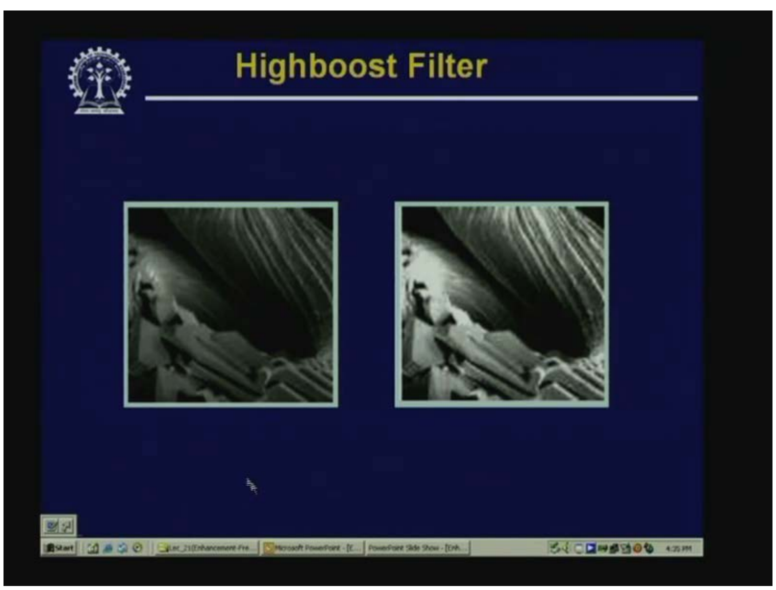
(Refer Slide Time: 51:13)



So, there we have said that in spatial domain; the high boost filtering operation, the high boost filtering output f (x, y) if I represent it if I represent this as f_{hb} (x, y) is nothing but A into f (x, y) minus f $_{lp}$ (x, y) and which is can be represented as A minus 1 into f (x, y) plus f high pass filtered output (x, y).

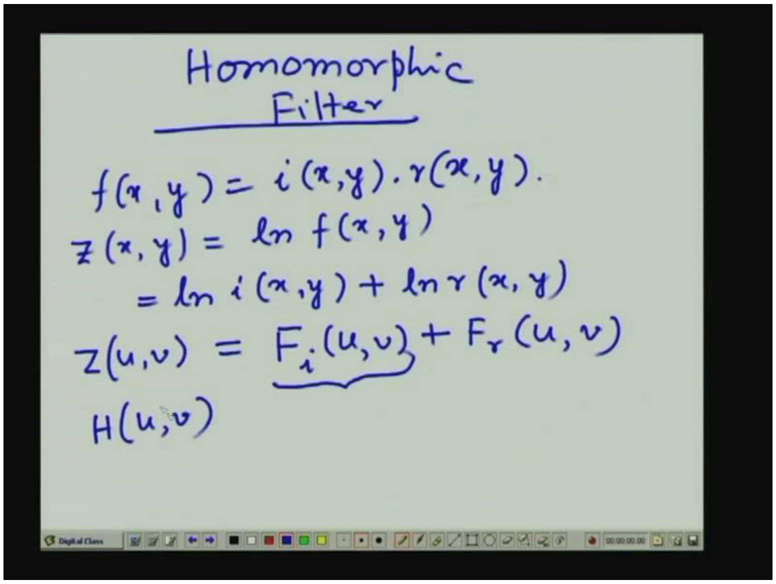
In the frequency domain; the corresponding operation, the corresponding filter can be represented by H_{hb} (u, v) is equal to A minus 1 plus high pass filter (u, v). So, this is what is the high boost filtered response in the frequency domain.

(Refer Slide Time: 52:32)



So, if I apply this high boost filter to an image, the kind of result that we get is something like this where again on the left hand side is the original image and on the right hand side, it is the high boost filtered image. Now, let us consider another very very interesting filter which we call as homomorphic filter, homomorphic filter.

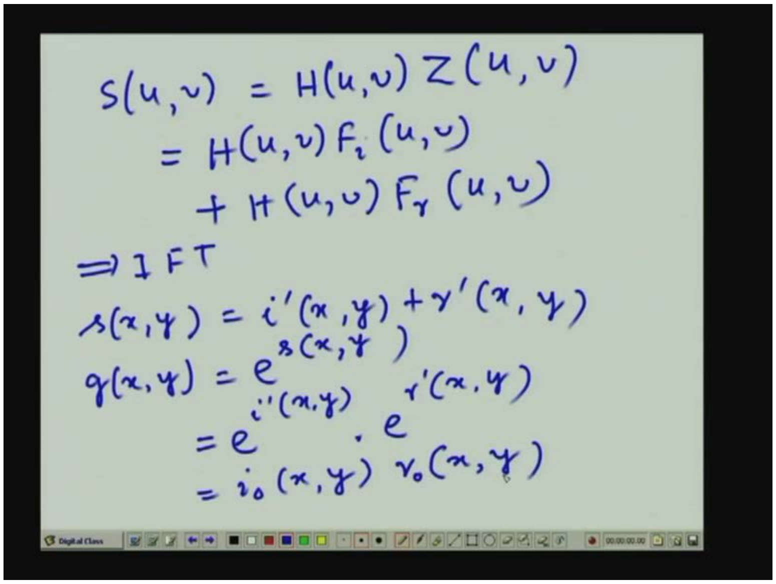
(Refer Slide Time: 52:52)



The idea aims from our one of the earlier discussions where we have said that the intensity at a particular point in the image is the product of 2 terms. One is the illumination term, other one is the reflectance term. That is f (x, y) we have earlier said that it can be represented by an illumination term i (x, y) multiplied by r (x, y) where r (x, y) is the reflectance term.

Now, coming to the corresponding frequency domain because this is the product of 2 terms; one is the illumination, other one is the reflectance, taking the Fourier transform directly on this product is not possible. So, what we do is we define a functions say z (x, y) which is logarithm of f (x, y) and this is nothing but logarithm of i (x, y) plus logarithm of r (x, y) and if I compute the Fourier transform, then the Fourier transform of z (x, y) will be represented by z (u, v) which will have 2 components F_i (u, v) plus F_r (u, v) where this F_i (u, v) is the Fourier transform of ln i (x, y) and F_r (u, v) is the Fourier transform of ln r (x, y).

(Refer Slide Time: 55:07)



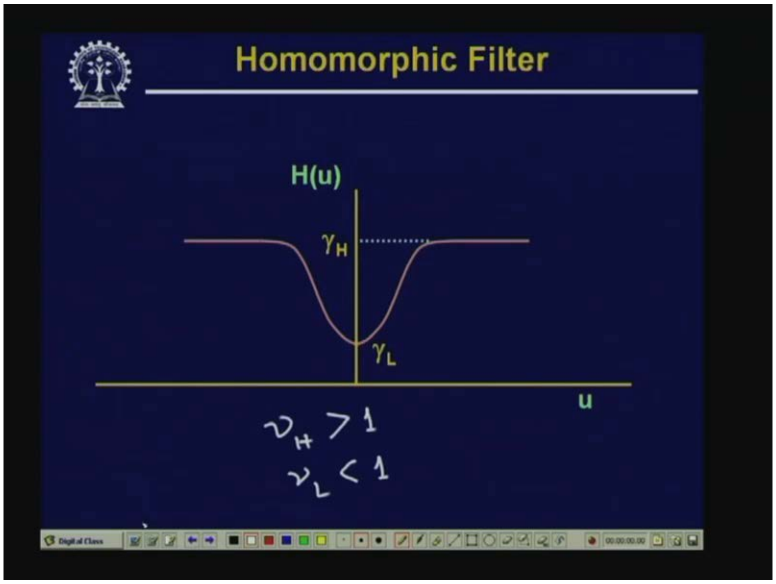
Now, if I define a filter say H (u, v) and apply this filter on this Z (u, v), then the output that I get is say S (u, v) which is equal to H (u, v) times Z (u, v) which will be nothing but H (u, v) times f_i (u, v) plus H (u, v) times F_r (u, v).

Now, taking the inverse Fourier transform, I get s (x, y) is equal to i dash (x, y) plus r dash (x, y) and finally I get g (x, y) which is nothing but e to the power s (x, y) which is nothing but e to the power i dash (x, y) into e to the power r dash (x, y) which is nothing but i_0 (x, y) into r out (x, y).

So, the first term is the illumination component and second term is the reflectance component. Now, because of this separation, it is possible to design a filter which can enhance the high frequency components and it can attenuate the low frequency components. Now, it is generally the case that in an image, the illumination components leads to low frequency components because illumination is slowly fairing whereas as the reflectance component leads to high frequency components, particularly at the boundaries of 2 reflecting objects.

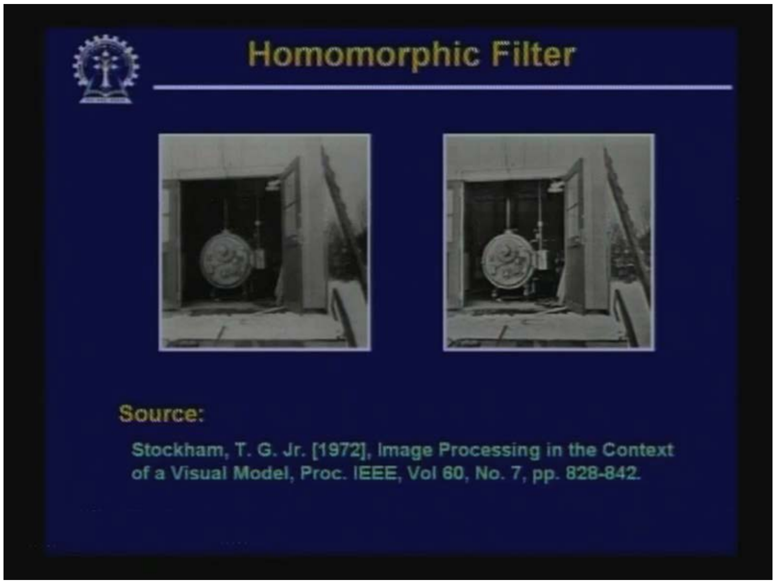
As a result, the reflectance term leads to high frequency components and illumination terms leads to low frequency components.

(Refer Slide Time: 57:13)



So now, if we define a filter like this a filter response like this and here if I say that I will have say gamma H greater than 1 and gamma L less than 1, this will amplify all the high frequency components that is the contribution of the reflectance and it will attenuate the low frequency components that is contribution due to the illumination. Now, using this type of filtering, the kind of result that we get is something like this.

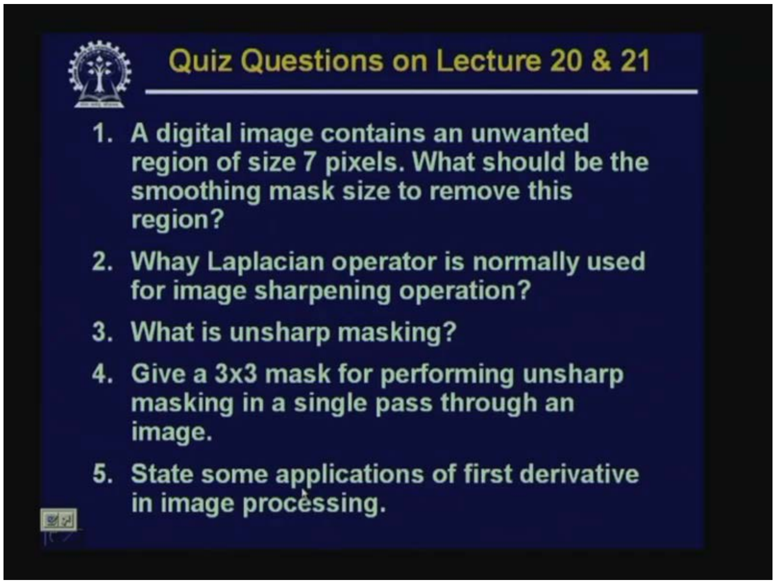
(Refer Slide Time: 57:46)



Here, on the left hand side is the original image and on the right hand side is the enhanced image. And if you look in the boxes, you find that many of the details in the boxes which are not available in the original image is now available in the enhanced image. So, using such homomorphic filtering, we can even go for this kind of enhancement or the illumination, the contribution due to illumination will be reduced. So, even in the dark areas, we can take out the details.

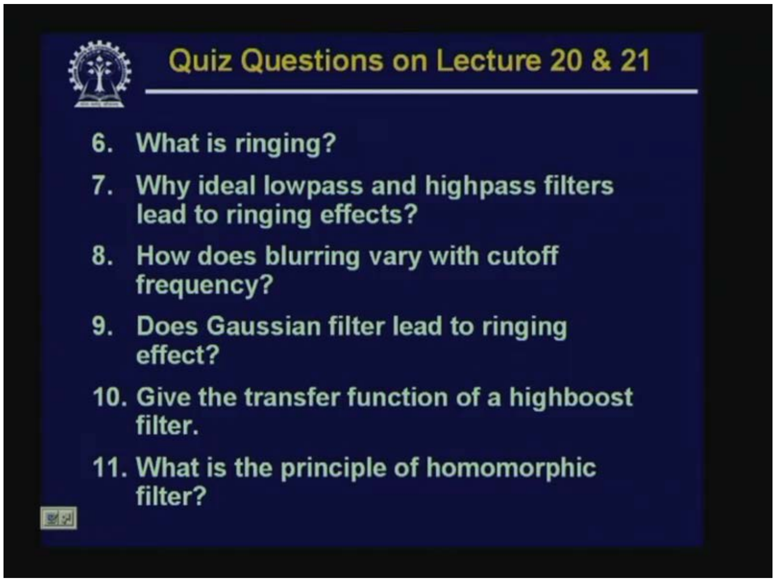
So with this, we come to an end to our discussion on image enhancements. Now, let us go to some questions of our today's lecture.

(Refer Slide Time: 58:28)



The first question is a digital image contains an unwanted region of size 7 pixels. What should be the smoothing mask size to remove this region? Why Laplacian operator is normally used for image sharpening operation? Third question - what is unsharp masking? Fourth question - give a 3 by 3 mask for performing unsharp masking in a single pass through an image. Fifth, state some applications of first derivative in image processing.

(Refer Slide Time: 59:18)



Then, what is ringing? Why ideal low pass and high pass filters lead to ringing effects? How does blurring vary with cut off frequency? Does Gaussian filter lead to ringing effect? Give the transfer function of a high boost filter and what is the principle of homomorphic filter?

Thank you.