Computer Vision and Image Processing Fundamentals and Applications

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Lecture 28

Interest Point Detection

Welcome to NPTEL MOOCs course on Computer Vision and Image Processing Fundamentals and Applications, I have been discussing about image features, today I am going to discuss about interest point detection. So, with the help of interest point I can do image matching that means the feature matching can be done with the help of interest point.

So, one example of interest point is the corner points. And with the help of this interest point I can do image matching, so for example in case of the stereo image matching I have to do matching between the left image and the right image, for stereo correspondence, so for this I have to consider some interest points and based on this interest point I can do matching. Another example I can give, suppose I have two images of a particular scene, so with these two images I can make a big image that is called the panoramic view.

So, I can join these two images to get a bigger image. So, for this I have to match these two images and after the matching I can join these two images, this is called the image stitching, so image stitching is important for panoramic view, for this also I have to do feature matching with the help of interest points. So, there are many applications of interest points like image alignment also I can use the interest points, for 3D reconstruction also I can use interest points.

So, I will be explaining all these concepts and one example already I have mentioned the corner points I can consider as interest points and also the interest points should be robust to affine transformation and also photometric variations. So, let us see the concept of the interest points and how to detect the interest points, so I will show with the help of interest point how we can match two images to find a correspondence between the two images, let us see the concept of the interest point.

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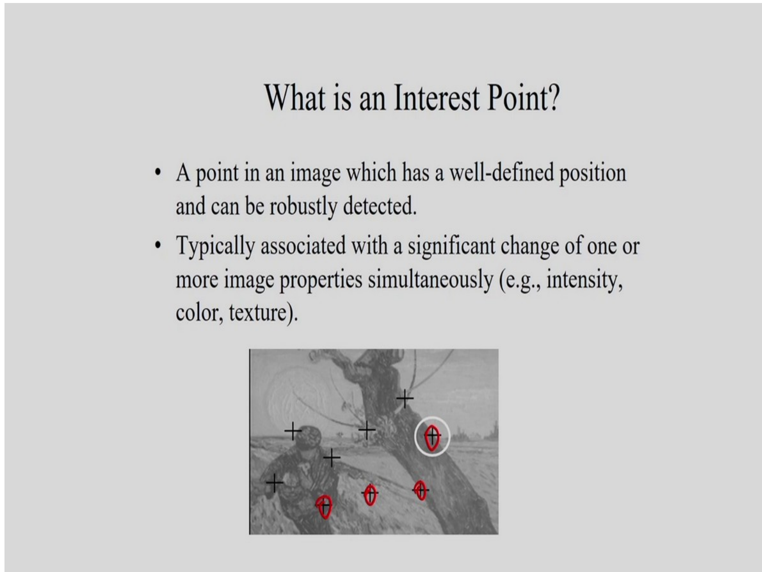

So, in this case, what is the definition of the interest point? A point in an image which has well-defined position and can be robustly detected that is the definition of the interest point. And in the interest point there is a significant change of one or more image properties simultaneously, so I can give one example suppose, intensity and colour may change in the interest point or colour and the texture may change in the interest point and already I have mentioned that the corner point is one example of interest point.

But the interest points could be more generic than the corner points. So, in this figure you can see I have shown some interest points, you can see these are the interest points and already I have mention, so in the interest point there is a significant change of one or more image properties simultaneously.

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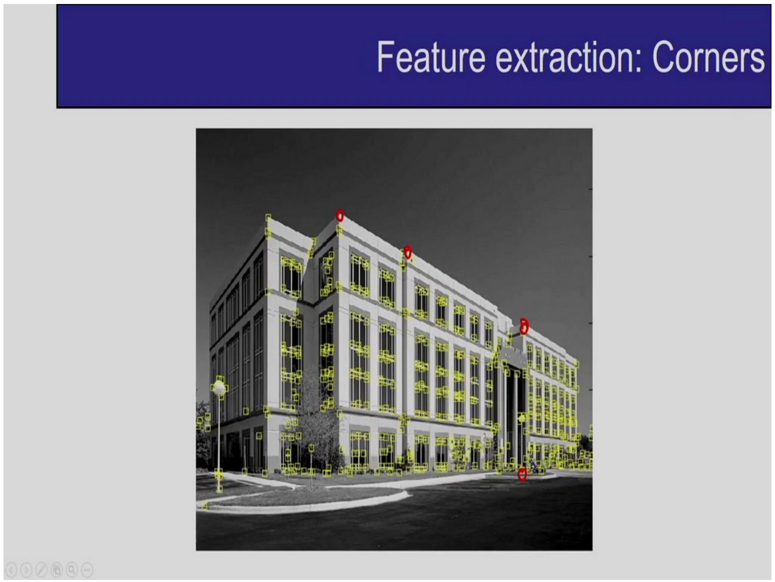

Now, you can see if I consider the corner points as interest points, you can see I have shown the corner points in the image you can see all the corner points present in the image.

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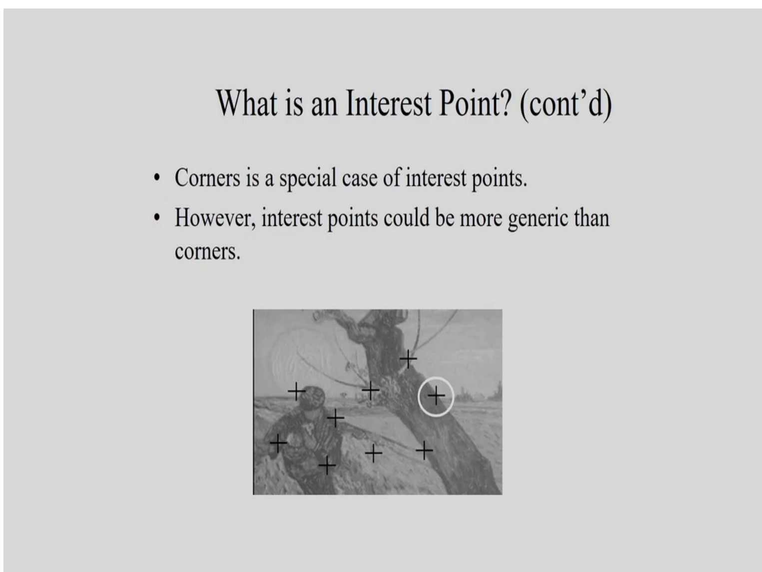

And one example already I have mentioned the corners is a special case of interest point, however the interest points could be more generic than the corner points. And one important property of the interest point is that it should be invariant to affine transformation like rotations, scaling, translation like this and also it should be robust to photometric variations.

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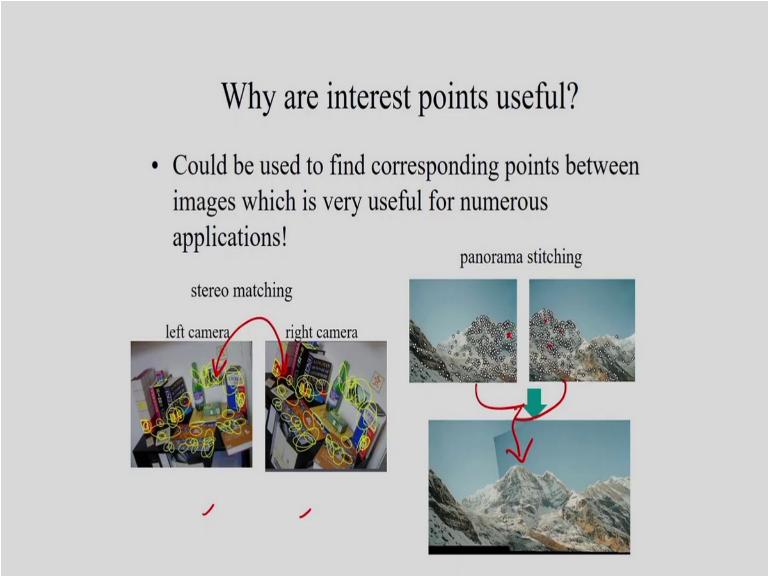

So, I can give this two examples why the interest points are important for image matching, you can see here at two images I am considering one is the left image another one is the right image, for finding the stereo correspondence and you can see I have some interest points and based on this interest points I can find the correspondence between the left image and the right image, that is for stereo matching.

In the second example I am considering the image stitching, so I have two images of a particular scene and I have considered some interest points, so you can see and based on this interest points I can find the correspondence between these two images and based on this I can join these together for a panoramic view. So, you can see from these two images I am making this image. So, this is the example of the image stitching.

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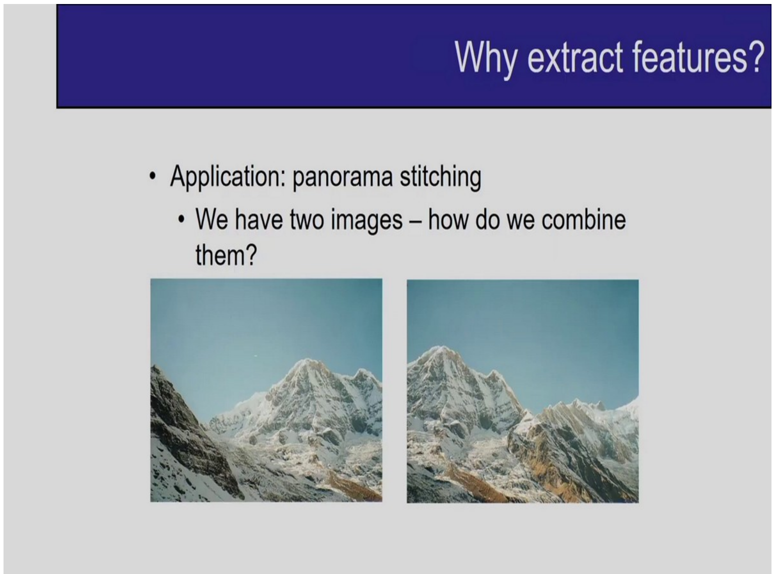

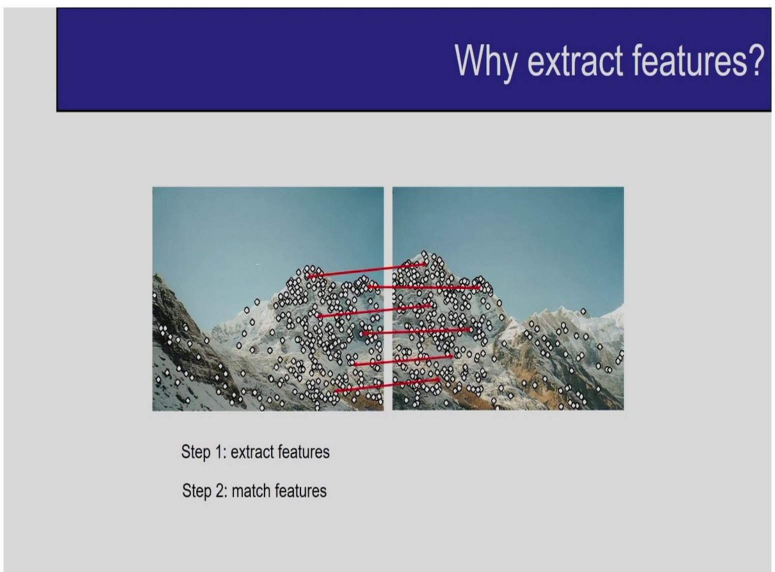

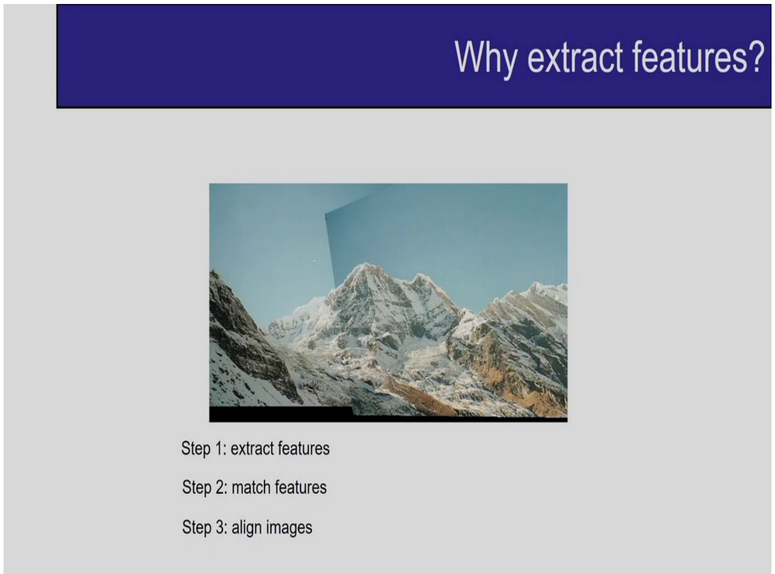

So, like this the panoramic stitching that is the image stitching and in this case, we have two images and how to combine them? So, already I have mention, so based on the interest points, I can find the correspondence between these two images and after this I can join these two images for panoramic view.

So, first I have to extract features these are the interest points and after this I have to do the matching of the features and finally I have to align the images, this is for image stitching. So, this is the method of image stitching, so first I have to extract the features and after this I have to match the features and finally I have to align images.

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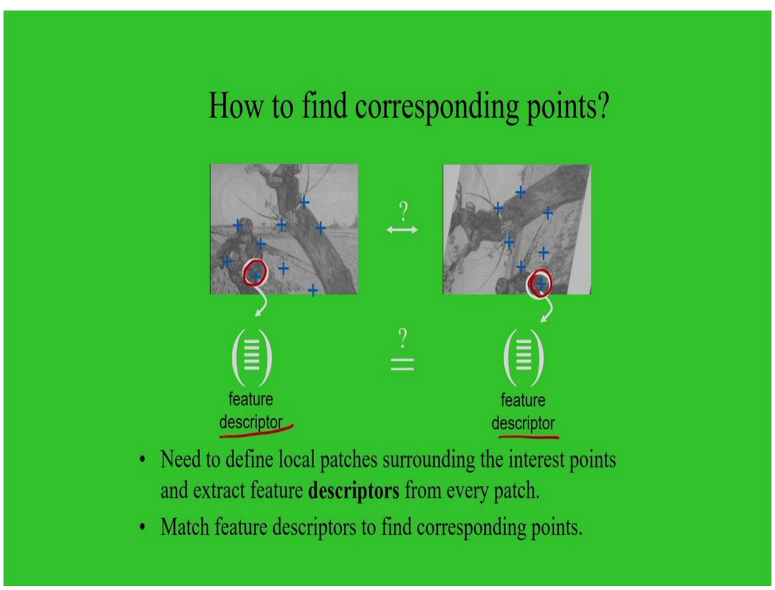

Now, in this case if I want to find the correspondence between these two images you can see one is the left image another one is the right image, so corresponding to this point you can see I am considering the feature and I am considering the feature descriptors and corresponding to the right image also I am considering one important point that is the interest point and corresponding to this I am considering the feature descriptors. So, first I have to extract feature descriptors from every patches of the image and after this based on these features I can find a correspondence between these two images that is nothing but the feature matching.

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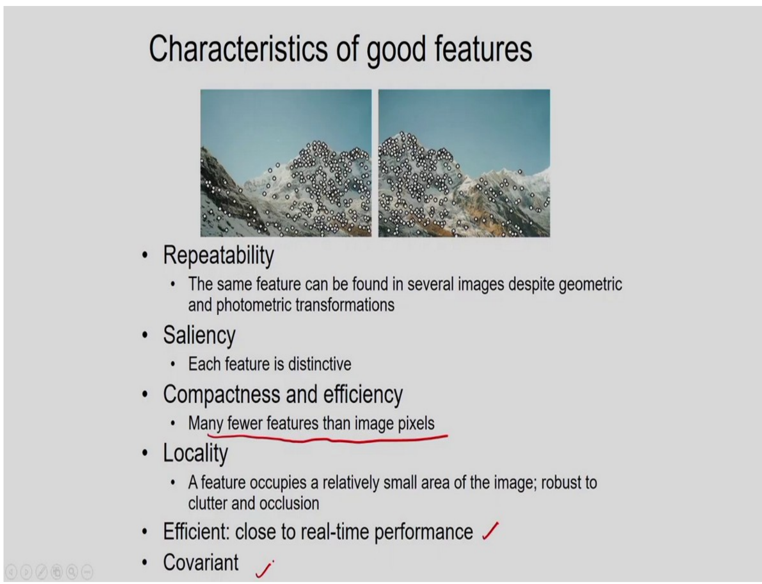

So, what are the characteristics of the good features? You can see I am considering the characteristics of a good features, the first one is repeatability, the same feature can be found in several images despite of affine transformation and the photometric variations. So, that is one important point, so we have to consider the affine transformations and also the photometric variations.

And in this case also the same feature should be found in several images, irrespective of affine transformation and photometric variations. Next one is the saliency, so each feature should be unique, that is the concept of the saliency. Another point is the compactness and the efficiency. So, we have only few features as compared to the image pixels, so by using these features we can represent the entire image.

So, instead of considering the all the image pixels, I can only consider few image features and with these features I can represent an image. Another point is that locality, so locality means it should be robust to clutter and occlusion, that is the concept of the locality and also it should be efficient for real time implementation. So, for real time implementation it should be computationally efficient. And the concept of the covariant I will be discussing in my next slides, so that is also very important, what is covariant?

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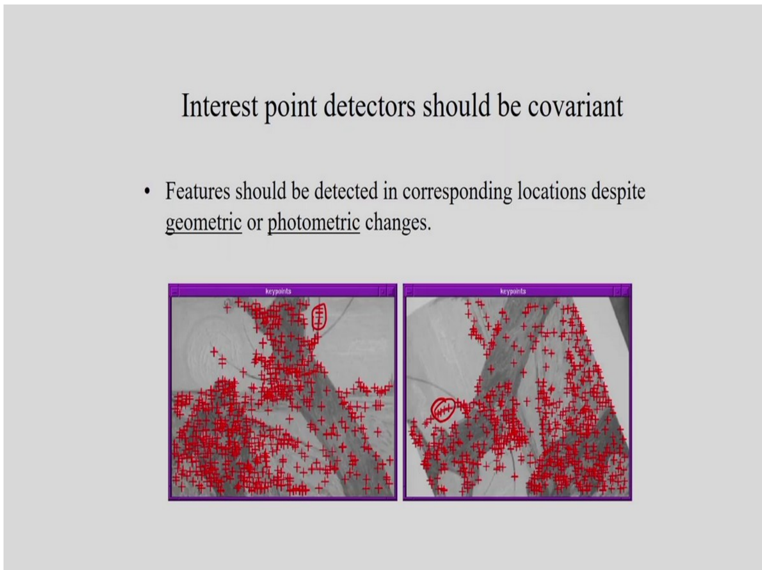

So, interest point detection should be covariant, that means the meaning is here you can see the feature should be detected in corresponding locations despite of geometry and the photometric change, so in this example I am considering the interest points and I am considering the geometric transformation and also the photometric variations.

So, despite of this variations in this case you can see the features I can detect in the corresponding locations. So, suppose if I consider in this figure you can see here, so corresponding to this portion you can see so I have the features here, this features, so that means the features should be detected in corresponding locations irrespective of geometry and the photometric variations.

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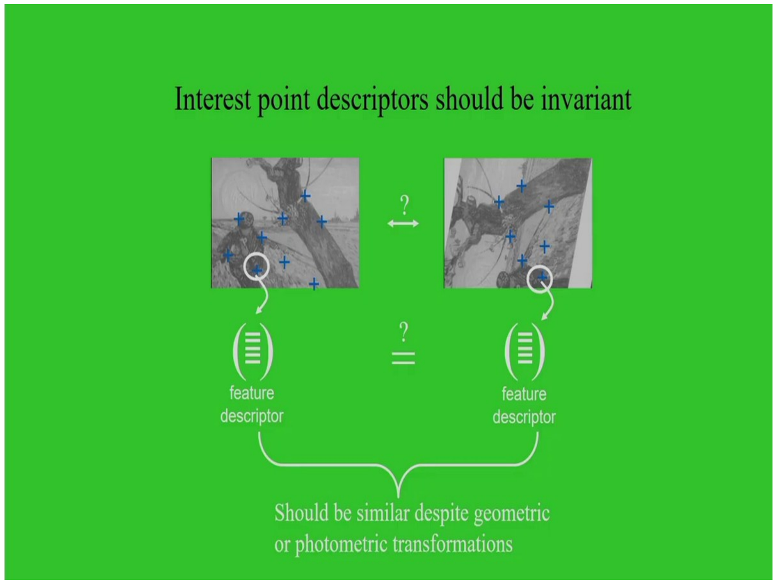

And interest point descriptors should be invariant, that is one point that is already I have mention, if I consider the interest points and that should be similar despite of geometric and the photometric transformation that is the concept of the covariant.

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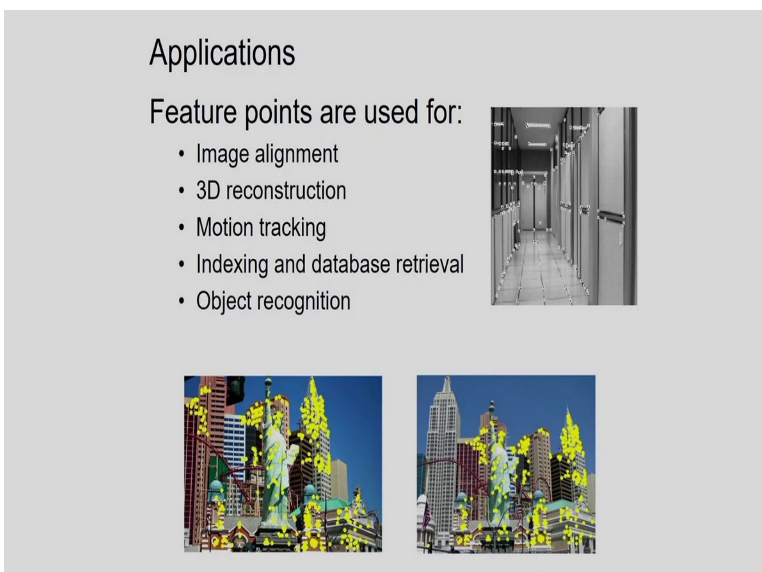

And already I have mention about the applications of the interest points, the applications maybe image alignment, so for these also I have to determine the interest points and based on this the interest points I can do image alignment. For 3D reconstruction one example, the motion tracking for motion tracking also I have to extract interest points and for indexing and for database retrieval that is nothing but the content-based image retrieval, so for content-based image retrieval, I can use interest points.

And finally for object recognition I can extract image features that means I can consider the interest points and based on this interest points I can do the object recognition. So, these are some applications of the interest points.

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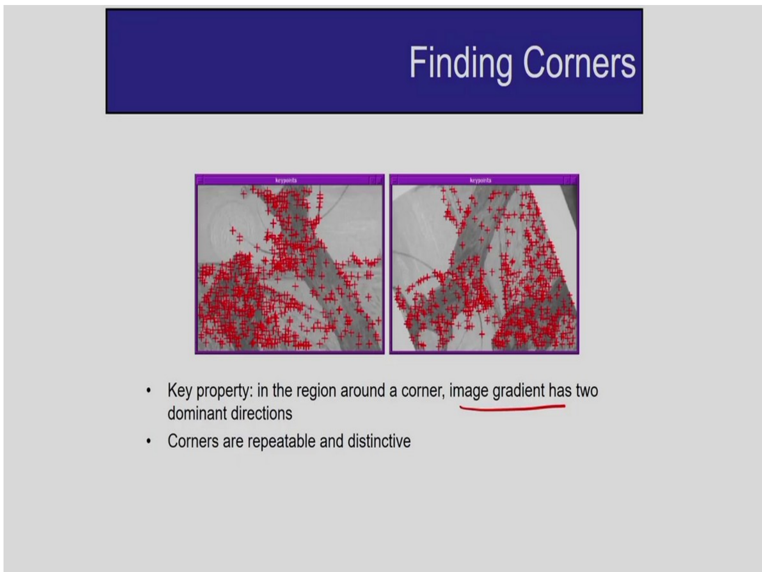

So, already I have mentioned the corner points I can consider as interest point, but the interest points could be more generic then the corner points. So, in this figure you can see the finding the corner points and in this case how to determine the corner points, so for this I have to determine image gradient, I can determine the image gradient along the x direction and along the y direction and based on this I can determine the corner points and the corners are repeatable and unique, so I will explain how to determine the corner points in my next slides.

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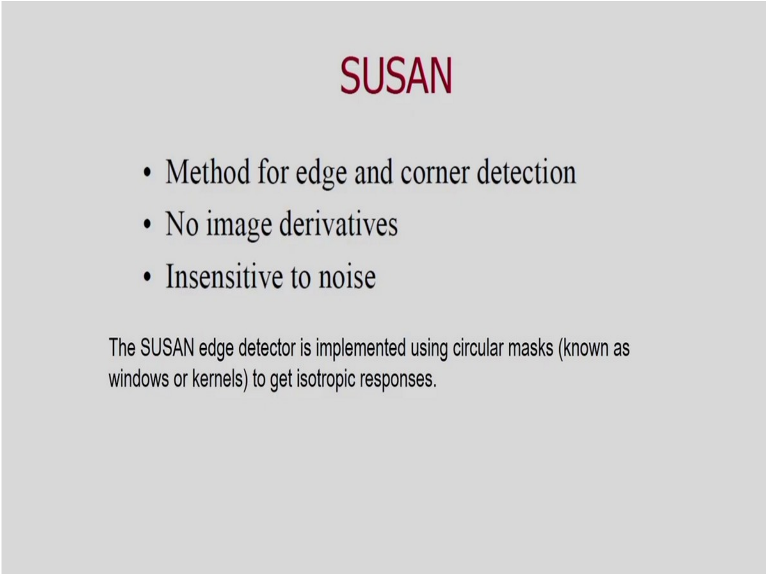

The first method I am going to discuss is the SUSAN corner detector. So, this is a method for edge and the corner detection and in this case I need not consider the image derivatives that means I need not compute image derivatives and also it is insensitive to noise, the SUSAN edge detector is implemented using circular marks that I can consider as windows or kernels to get the isotropic responses.

So, for the SUSAN edge detector I need circular mask and this I can consider as windows or the kernels to get isotropic response. Isotropic response means the property do not vary in magnitude according to the directions of implementation. So, that is the concept of the isotropic response that is the property do not vary in magnitude according to the direction of implementation. So, let us see the concept of the SUSAN corner detector.

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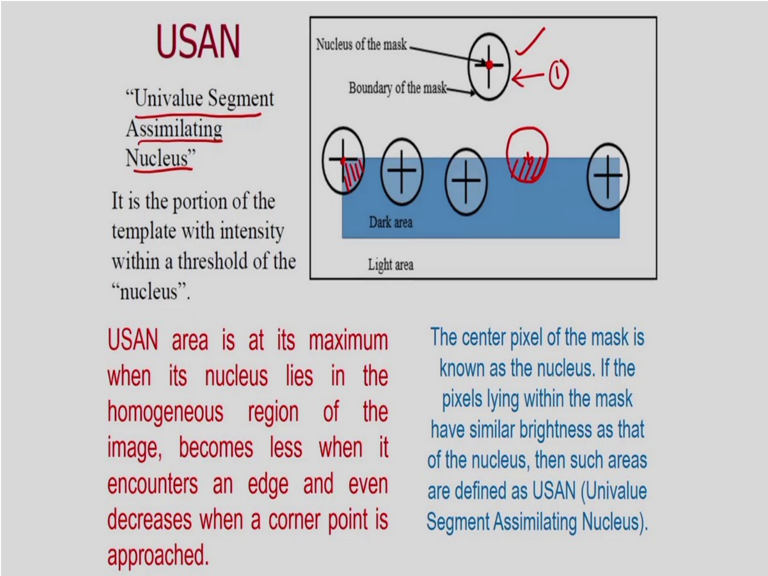

So, it is SUSAN corner detector it is used to determine whether a pixels lying within the mask have similar brightness as that of the nucleus. In this case, I have shown the SUSAN mask if you see in the figure, so the central pixel of the mask is called a nucleus. So, if I consider this mask, so this is called a nucleus of the mask.

If the pixels lying within the mask have similar brightness as that of the nucleus, then such areas are defined as Univalue segment assimilating nucleus that is called the USAN. So, what is the meaning of the USAN? USAN means the unique value segment a simulating nucleus that is called the USAN. So, it is the portion of the template with intensity within a threshold of the nucleus. So, that is the concept of the USAN.

So, that means it is used to determine whether the pixels lying within the mask have similar brightness as that of the nucleus. Now, in this case if you see the in this figure, so I am considering three cases suppose the USAN is here at this point, the point is supposed the first position is one that is nothing but the homogeneous region. In the homogeneous region, the USAN area is maximum, so if you see the homogeneous region the corresponding to the point one suppose the USAN area will be maximum.

And suppose corresponding to the edge I am putting the USAN here and you can see the nucleus, so you can see corresponding to the edge pixel the USAN area will be less as compared to USAN area corresponding to the homogeneous region. So, in the edge is you can see the USAN area will be half, so USAN area will be half. And if I consider the corner points, if you see the corner points, the USAN area will be minimum as compared to the edge. So, based on this concept I can determine the corner points, based on the USAN area. So, in my next slide mathematically how to consider this problem, you can see.

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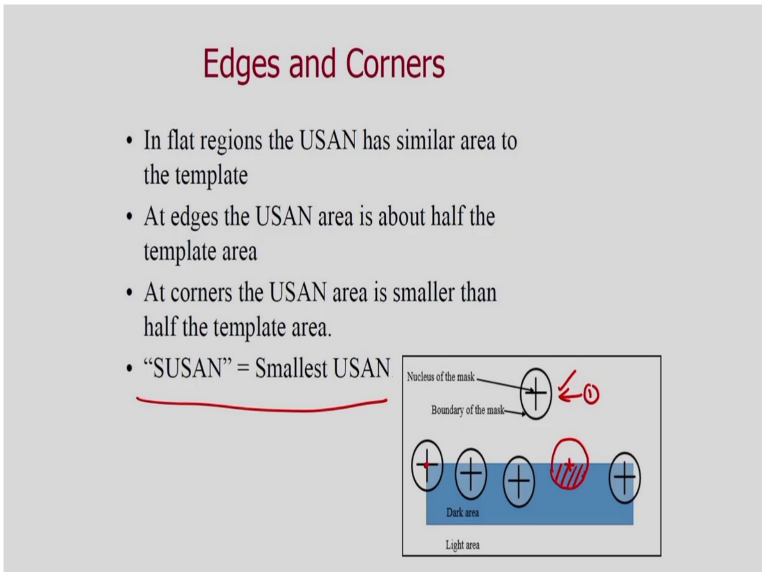

So, in the flat regions that means in the homogeneous region, the USAN has a similar area to the template, so corresponding to this case the case number one, at the edges if I consider the edges the USAN area is about the half of the template area, so that means if I put the mask here and this is my nucleus then you can see the USAN area is about half the template area. And if I consider the USAN at the corner so at a corner points at the corners the USAN area is smaller than the half of the template area.

So, I am repeating this at corners the USAN area is smaller than half the template area. And what is SUSAN? SUSAN means smallest USAN and that is the meaning of the SUSAN, the SUSAN means the smallest USAN. So, based on this concept I can determine the corner points. So, mathematically how to explain this concept?

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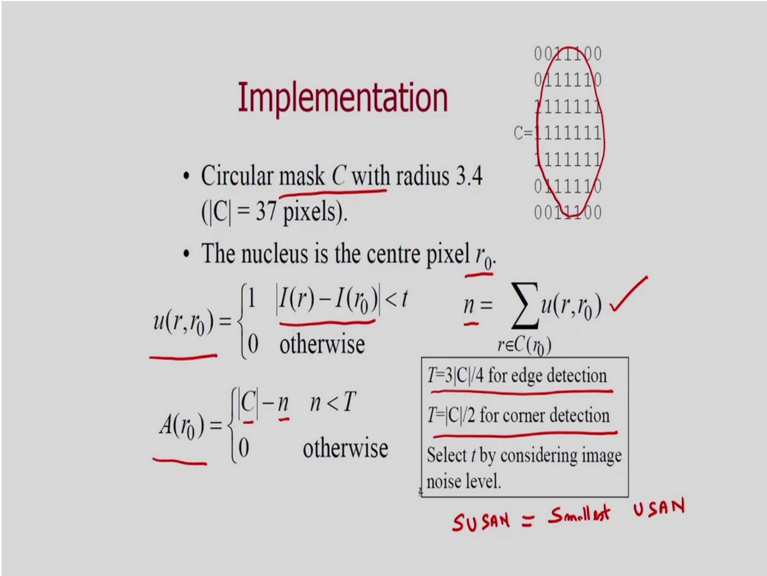

You can see here. So, for this I am considering one circular mask having 37 pixels, so C is the circular mask I am considering and you can see it is a circular mask, I am considering having 37 pixels. The nucleus is at the centre pixel, the centre pixel is r naught, now in this case I am considering this u r, r naught that is equal to 1, if this difference that deference is I r minus I r naught is less than a particular threshold, otherwise it is 0.

So, what is the meaning of this? It is used to determine the portion of the template which intensity within a threshold of the nucleus, so that I am considering that is u r comma r naught, after this I am just counting this, I am just doing the summation that means I want to find the total area and finally I am considering the A r naught that is the area I am determining, it is used to find the USAN area.

So, I am finding the USAN area based on this because already I have calculated n and C means the 37 pixels I am considering and you can see for edge detection I can consider this threshold and for the corner detection I can consider threshold C divided by 2. So, in flat region USAN has a similar area to the template that already I have explained at edges the USAN area is about half of that template area, that is the concept of USAN.

And at the corners the USAN area is smaller than half the template area. And in this case the SUSAN means you can see what is the SUSAN already I have explained the smallest USAN.

What is USAN? That is univalue segment assimilating nucleus that is USAN. So, SUSAN means the smallest USAN. So, this is about the implementation of the SUSAN corner detector.

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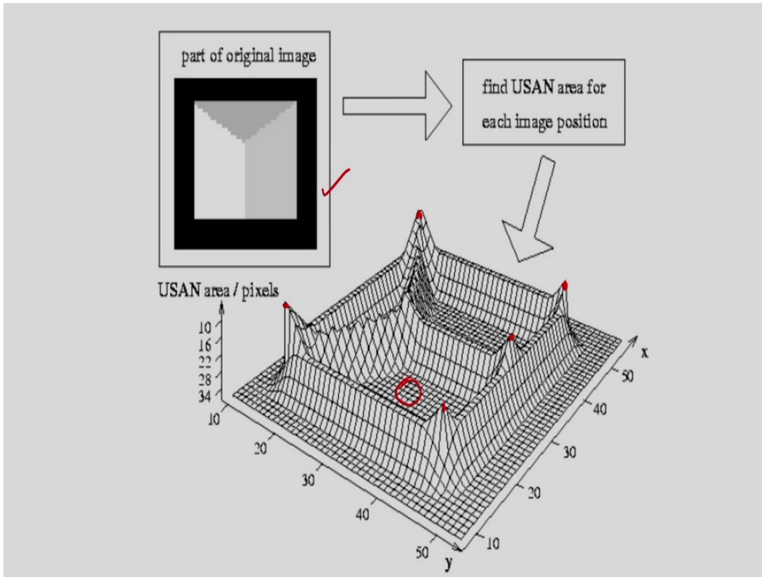

And you can see in this example I am considering one binary image and I am finding the USAN area for each image position, so you can see for a corner points the area is minimum you can see the area of the USAN I am determining and this is the area corresponding to the flat portion of the image. So, based on this I can determine the corner points.

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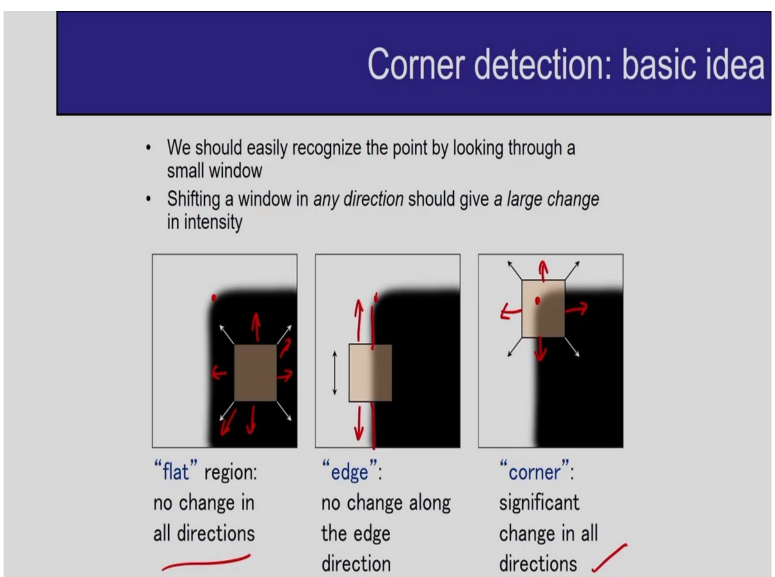

And after this I will discuss some other techniques for determining the corner points, so you can see here I am considering one window, this window I can move in any direction and in this case I am considering the this window that is the shifting window I am considering and in this case I am finding the change in the intensity. So, here you can see in this image this is the corner, you can see this is the corner position, so if I move the windows in any direction within the flat region, then in this case there is no change in intensity in all the directions.

So, I can move the window in this direction, I can move the window in this direction, I can move the window in this direction like this I can move the window in all the directions I can move and corresponding to the homogeneous region that is the flat region there is no change in intensity in all directions. And corresponding to the edge you can see in the second figure no change along the x direction. So, if I consider this is edge, so if I consider edge and if I move the mask or the window in this direction, then in this case you can see the no change along the x direction.

But corresponding to this corner points you can see, if I move the window or if I move the this mask in all the directions I can move the mask in this direction in this direction all the directions what I am getting a significant change in intensity in all the directions I will be observing. So, corresponding to the corner point you can see the significant change in intensity in all the directions I will be getting. So, that is the concept of the corner point detections by considering a window.

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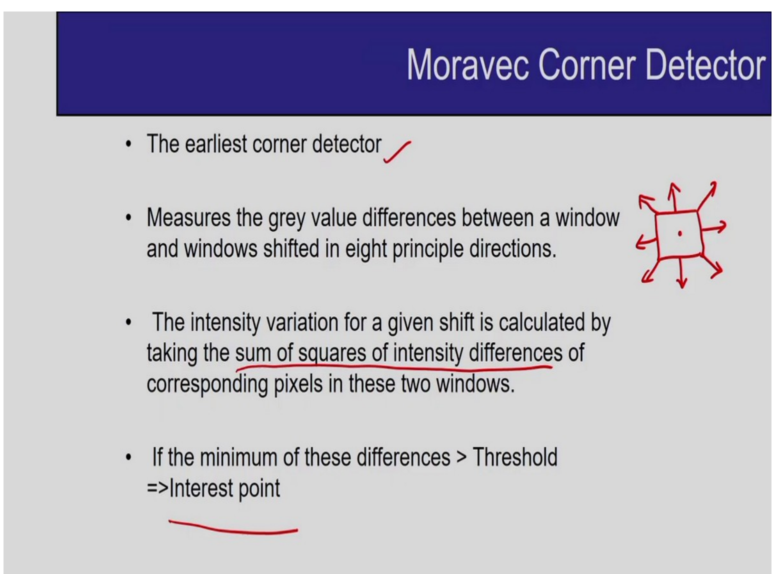

So, first the corner detector, I am discussing that is the more Moravec corner detector, so the earliest corner detector is the Moravec corner detector and in this case, what concept I am considering? Measures the grey value difference is between a window and windows shifted in eight principle directions.

So, that means that window is shifted in eight directions, so if I consider suppose this is the window and this is the central pixel, so I can move the windows in eight directions like this, in all the eight directions I can consider the moment. And the intensity variation for a given shift is calculated by taking the sum of squares of intensity difference of corresponding pixels in this two windows.

So, that means I am determining the intensity difference and in this case I am considering the sum of square intensity difference I am calculating. After this what I am considering? If the minimum of these differences is greater than a particular threshold that corresponds to an interest point. So, that means I am considering the intensity differences, I am determining based on this that directional window the window I am moving in all directions and after this I am determining the intensity differences and if the minimum of these differences is greater than a particular threshold that corresponds to a particular interest point that is nothing but the corner point.

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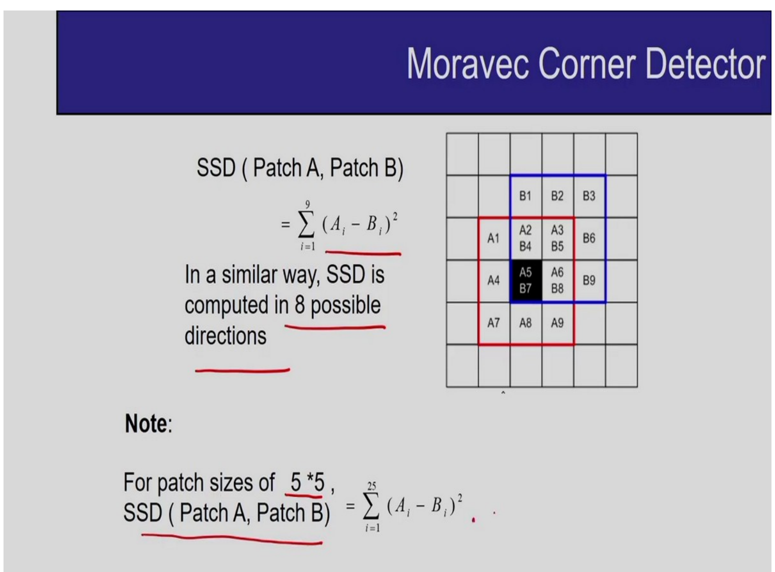

So, mathematically you can see this concept, I am considering patch A and the patch B and I am determining SSD the sum square distance I am considering and you can see eight possible directions I am considering here and you can see I am determining the SSD between patch A and the patch B. And if I consider the patch size 5 by 5 the 5 cross 5 then SSD between patch A and the patch B I can determine like this.

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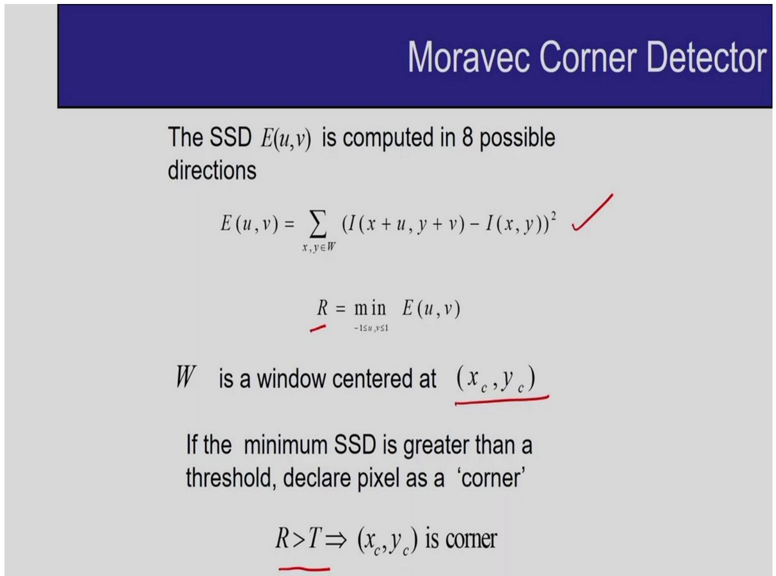

So, SSD that is E u v I can compute for 8 possible directions like this and in this case I am determining the response, the response is nothing but the minimum of E u v and the W that is the window is centered at the point, the point is xc comma yc and if the response is greater than a particular threshold that corresponds to the corner points.

So, this is the concept of the Moravec corner detector. So, I have to find a SSD that indicates the intensity changes, the intensity difference that I am observing for 8 directions and based on this I am considering the response, the response is the R, if the response is greater than a particular threshold that corresponds to the corner points.

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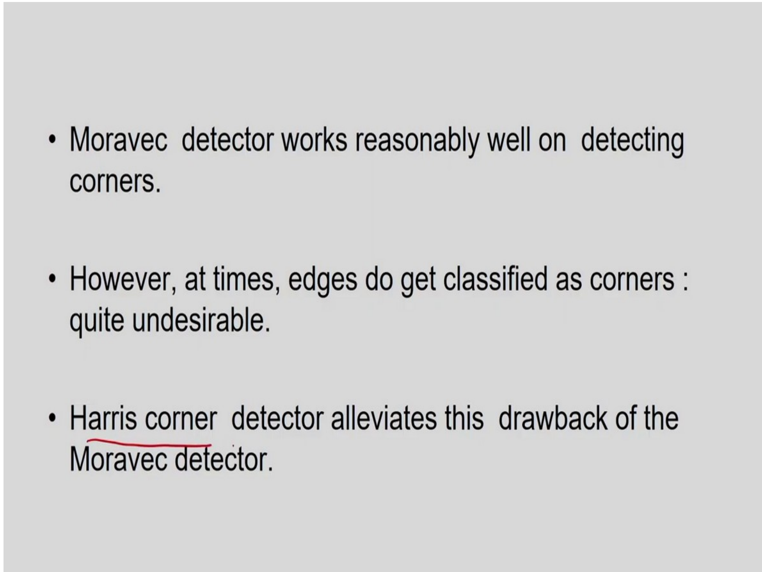

So, it is a good corner detector, but sometimes we have the false positives edges are detected as corners that is the problem of the Moravec corner detectors. So, for this we can consider another detector the corner detector that is the Harris corner detector.

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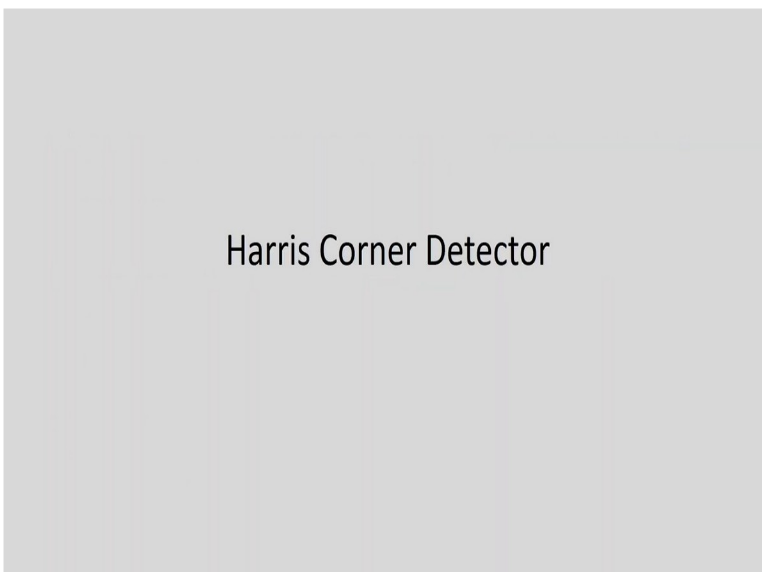

So, now I will discussed the concept of the Harris corner detector.

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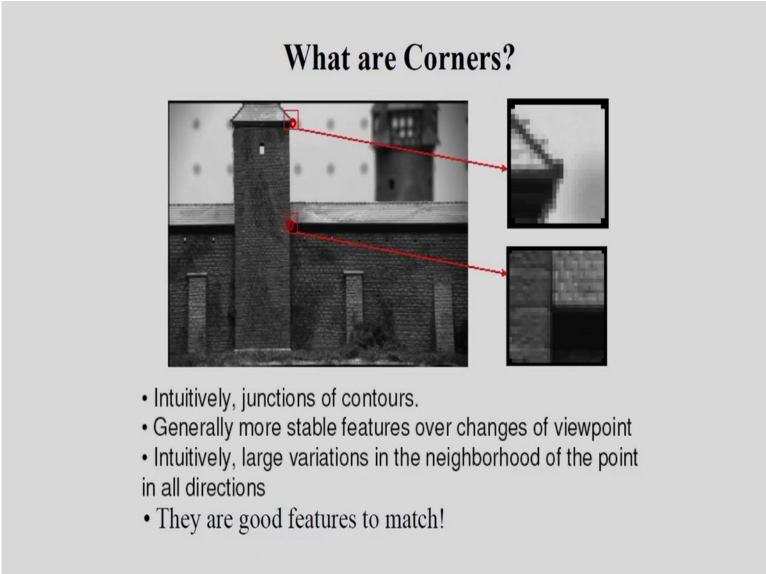

So, already I have defined a corners, the corner points are more stable features over changes of viewpoint. And in this case how to detect the corner points? The concept already I have explain, so if I consider one window, so in the corner points we can observe the large variation of intensity change and based on this we can determine the location of the corner points. So, in this figure you can see I have shown the some corner points like this, some of the corner points you can see. So, based on this corner points we can do the image matching.

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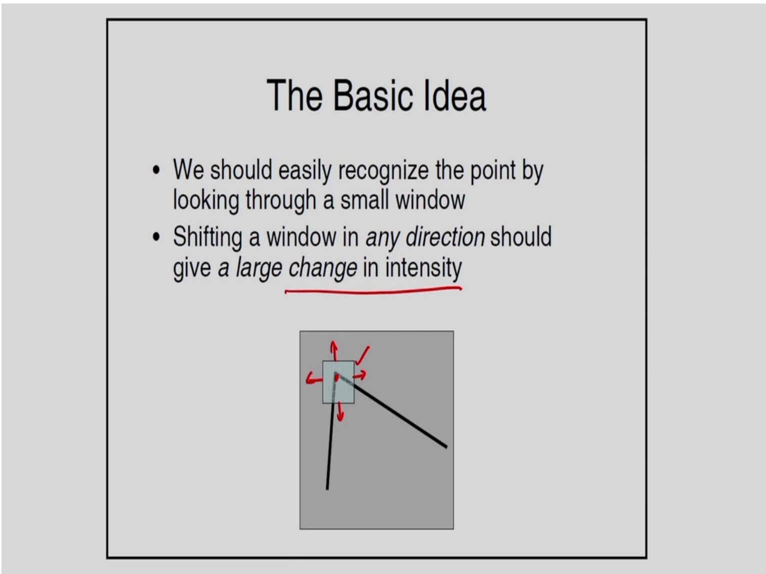

So, the basic idea is like this, so we should easily recognize the point by looking through a small window. So, one window I am considering, so small window I am considering and suppose this is the centre point of the mask the window and I am shifting the window in any directions I can shift the window in this direction in all the directions I can shift the window.

Now, I am observing the change in intensity. So, corresponding to the corner points we have a large change in intensity and that is important and based on this we can determine the corner points that is corresponding to corner point there is a large change in intensity.

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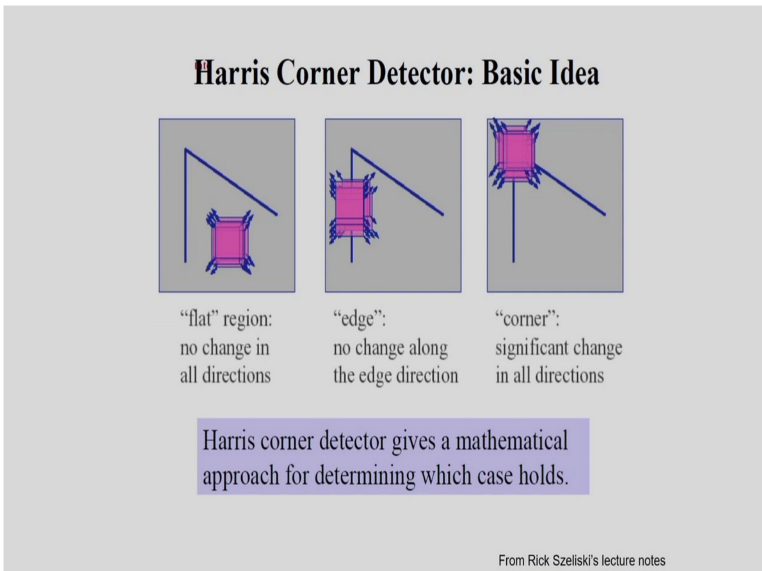

So, this concept again I am explaining here, so corresponding to the flat region a no change in all the directions, no change means no change in the intensity in case of the edge no change along the x direction that concept already I have explained and corresponding to the corner points significant change in all the directions. And based on this concept we can develop the mathematical concept behind the Harris corner detector. So, Harris corner detector is based on this principle.

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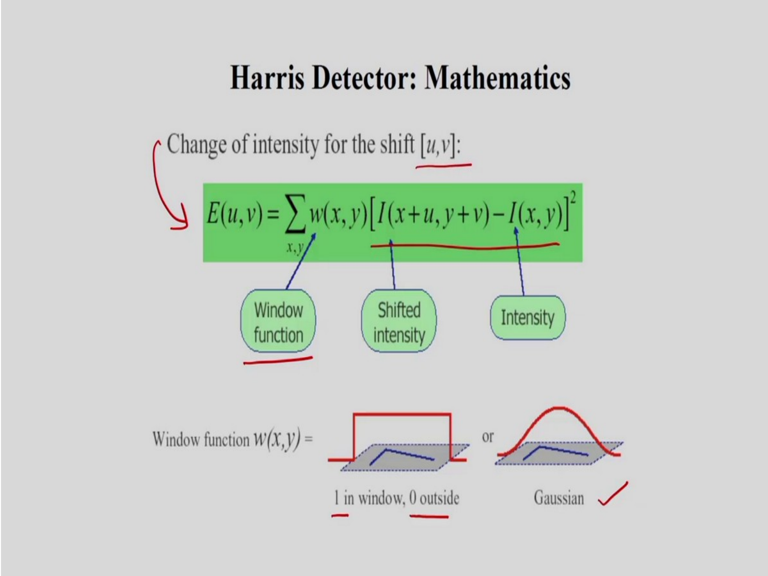

So, mathematically how to represent the Harris corner detector, you can see mainly we are observing the change of intensity for a particular shift, so I am considering the shift u and v, u is the spatial shift in the x direction and v is the spatial shift in the y direction and I am considering the change of intensity I am determining here that is nothing but E u v I am determining and I am considering the window function, the window function is w x comma y.

So, this window function I am considering, so if I evaluate E u v within this window, then I have to consider 1 and if it is outside the window then in this case it will be 0. So, that the Gaussian function I can consider as also window, I can consider a Gaussian function as a window. Now, in this case if you see this expression, what is the meaning of this expression? I am actually determining the change of intensity between two image points. So, for this what I am considering? I am shifting that window and I am determining change of intensity for a particular shift.

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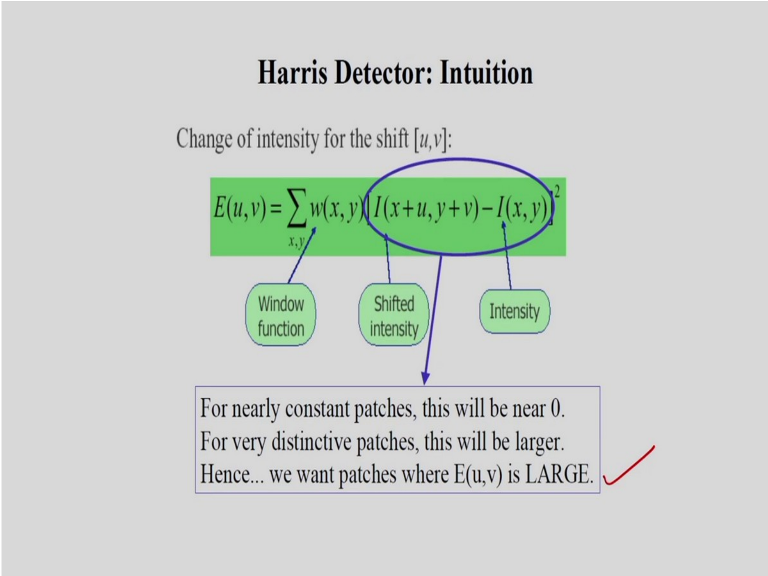

So, you can see for nearly constant patches has this change of intensity will be 0 almost 0 and for very distinctive patches this will be very large that is the change of intensity will be very large. So, that means for the corner points E u v will be very high. So, that is why we want patches where E u v is large. That is the change of intensity for a particular shift will be large corresponding to a corner point.

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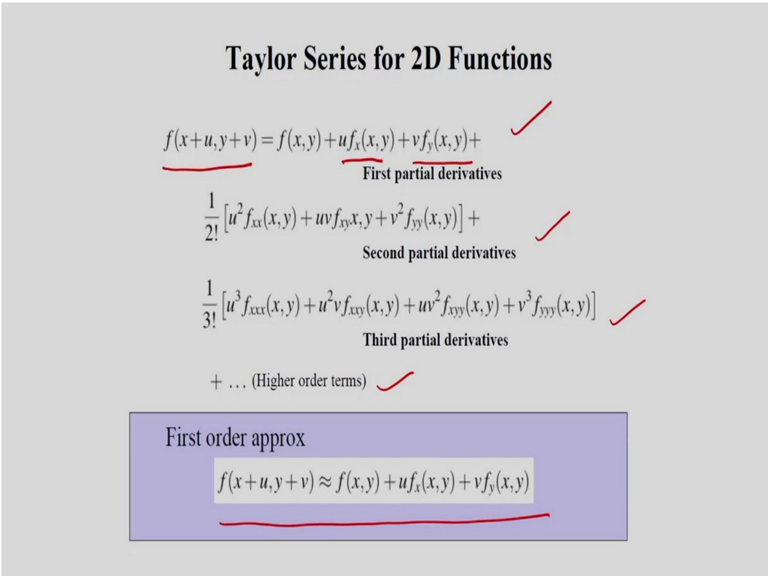

And for this you can see I am considering the Taylor series approximation, so if I consider f x plus u comma y plus v, so with the help of the Taylor series expansion I can write like this f x y plus u fx x comma y that is nothing but the gradient along the x direction fx means the gradient along the x direction and vfy xy, what is fy? fy is the gradient along the y direction, that is the first order derivative.

And after this I am considering the second order partial derivative the third order partial derivatives and also the higher order terms I am considering corresponding to the Taylor series expansion. And I can approximate this one by neglecting the second order derivative and all the higher order derivatives I can neglect, so based on this I can do the approximation, so f x plus u comma y plus v is approximately equal to f x comma y plus u the gradient along the x direction plus v fy xy that is the gradient along the y direction. So, this is the Taylor series approximation for 2D functions.

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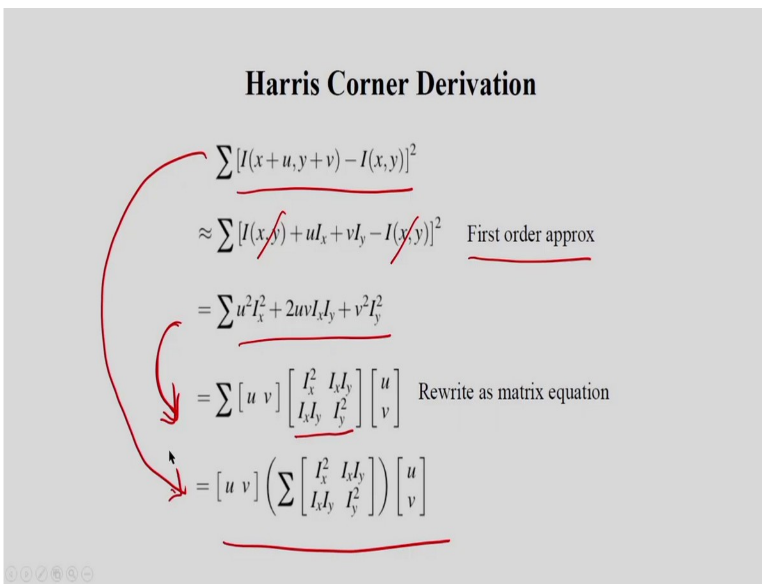

So, based on this approximation you can see the change in intensity between two patches and I am considering the first order approximation you can see, so it is I xy plus uI x plus b Iy minus I x comma y whole square I can consider and after this you can see I can cancel this one this and this I can cancel and finally, what I will be getting? I will be getting u square into Ix square plus twice uv Ix iy plus b square Iy square that I will be getting.

And I can write the matrix equation in this from here you can see, so u v and I am considering this matrix Ix square Ix Iy Ix Iy Iy square that is the matrix and after this u v I am considering so this expression I can write in the in the form of the matrix equation like this and I will be getting this one. So, this is the expression for the change in intensity I will be getting. So, corresponding to this I will be getting this one.

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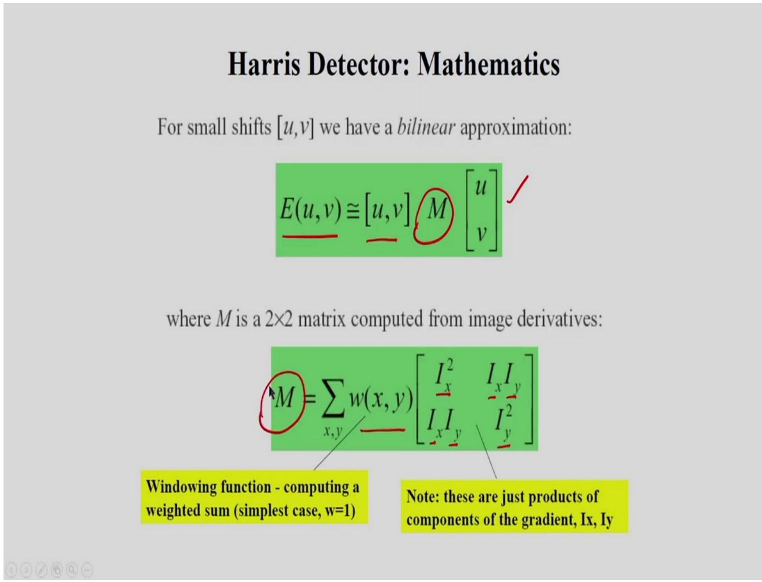

So, you can see there by considering that approximation I can write E u v is approximately equal to that u v M matrix, M is I am considering that matrix already I have defined in my last slide and u v you can consider like this. So, what is this matrix M? The matrix m is nothing but Ix square Ix Iy, Ix Iy, Iy square, what is Ix? Ix is nothing but the gradient along the x direction. And what is Iy? Iy is nothing but that is the gradient along the y direction.

So, that is the matrix M is computed from the gradient the matrix m is computed from the gradients and again you can see I am considering the window function, so that window function w is equal to 1, but a simple cases and you can see what is the matrix M, this is the nothing but the matrix M is obtained from the image gradients.

So, in this case I am calculating E u v and for nearly constant passes the E u v will be approximately equal to 0 and for the distinctive patches this will be large, that is the E u v will be large. So, that is the concept of the E u v and in this case I have to determine term matrix M and that is computed from image gradients.

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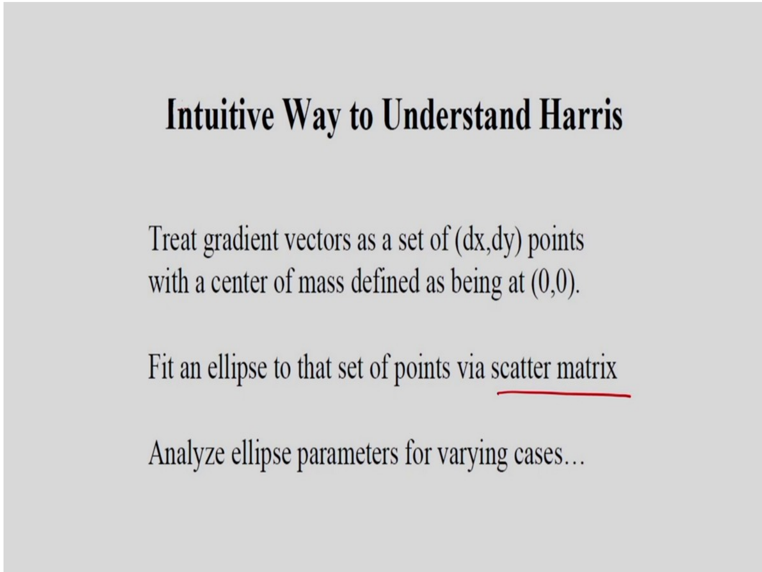

So, this concept already I have explain and in this case I have to compute the image gradients the gradient along the x direction and the gradient along the y directions and in this case I have to consider the ellipse fitting the I have to consider the scatter Matrix depth concept I am explaining in my next slide what is the scatter matrix and how to fit an ellipse. So, you can see this one.

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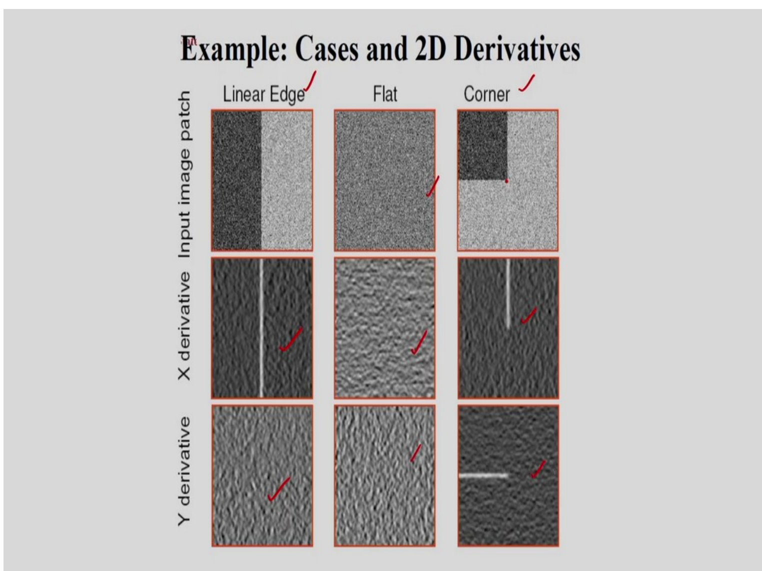

So, the concept is like this if I consider these images I am considering the first image is the linear is I am considering the second image with a flat image that is the homogeneous image almost and third one I am considering the corner, one corner point I am considering. So, corresponding to the linear is if you see the x derivative, so I will be getting the x derivative like this and this is the y derivative corresponding to the linear edges.

And if I consider the flat region, so for the flat region also I can determine the x derivative and the y derivative like this and corresponding to the corner points you can see I have this x derivative the first one is the x derivative and second one is the y derivative I can determine. So, based on this I have to determine the corner points.

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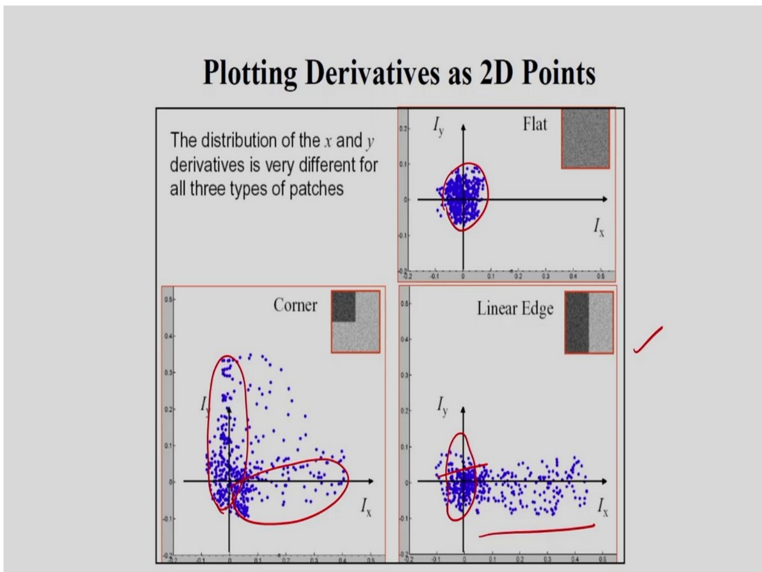

And you can see corresponding to the flat region the gradient along the x direction and the gradient along the y direction there will be very small and in this case it will be centered around the origin like this, corresponding to the flat region. Corresponding to the linear is the gradient along the x direction will be high and gradient along the y direction will be less. So, this is the gradient along the y direction and this is the gradient along the x direction.

So, corresponding to the linear is the gradient along the x direction will be high and gradient along the y direction will be less. And corresponding to the corner points if I consider the both the gradients that is the gradient along the x direction will be high and the gradient along the y direction will be high.

So, based on this gradient information I can determine the corner points that means for the corner points both the gradients will be high for the flat region both the gradients will be low. And for the linear is suppose in this case I am considering this linear is that is the vertical is the x gradient will be more and the y gradient will be less.

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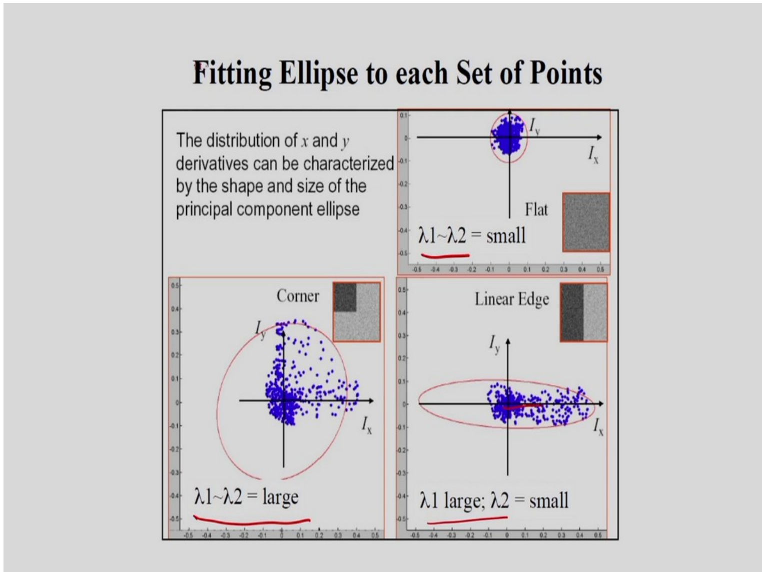

Now, corresponding to this gradient points I can fit an ellipse, so corresponding to the first case you can see this I can fit a circle here, now I can fit ellipses to each set of points, the points corresponding to the gradients along the x direction and the gradient along the y directions. So, corresponding to the flat region you can see I am fitting the ellipse, but in this case the major axis and the minor axis of the ellipse will be same almost same because the gradient will be small along the x direction and along the y direction, so that is why the lambda 1 and lambda 2 will be small.

What is the lambda 1 and lambda 2? The lambda 1 and lambda 2 are the eigenvalues I am considering so that I am going to explain, but you can see in the scatter plot in the corresponding to the flat region the gradient of x direction and the gradient of y direction will be less and in this case you can see I am fitting the ellipse. In case of the corner points, you can see the lambda 1 and the lambda 2 will be large and corresponding to the linear is you can see if I fit the ellipse the lambda 1 is large that is nothing but the major axis will be large, you can see the major axis and the minor axis will be small.

So, in case of this eigenvalues, the major axis corresponds to the eigenvalue lambda 1 and the minor axis corresponds to the eigenvalue lambda 2. So, in case of the flat region, lambda 1 and lambda 2 will be small and in case of the linear is that is the vertical is this lambda 1 corresponding to the major axis will be high and corresponding to the minor axis is the lambda 2 will be small. And in case of the corner points you can see both lambda 1 and lambda 2 will be large.

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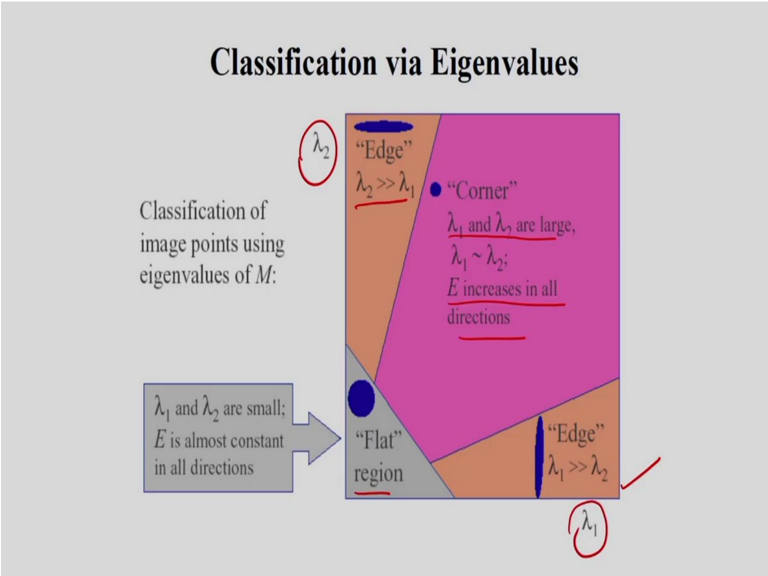

Based on this concept I can do classification with the help of the eigenvalues. So, eigenvalues means if I consider the ellipse the major axis of the ellipse corresponds to the lambda 1 eigenvalue and the minor axis corresponds to the eigenvalue lambda 2. And in this case you can see corresponding to the flat region lambda 1 and lambda 2 are small and each almost constant in all the directions.

And corresponding to the vertical edge if you consider corresponding to the vertical edge the lambda 1 is greater than lambda 2, so in the x direction I am plotting lambda 1 and in the y direction I am plotting lambda 2. And corresponding to the horizontal is the lambda 2 will be greater than lambda 1.

And corresponding to the corner points both lambda 1 and lambda 2 will be large that means E increases in all the directions. So, based on this concept based on the eigenvalues I can determine the vertical edge, I can determine the horizontal edge, I can determine the flat region but mainly I can determine the corner points.

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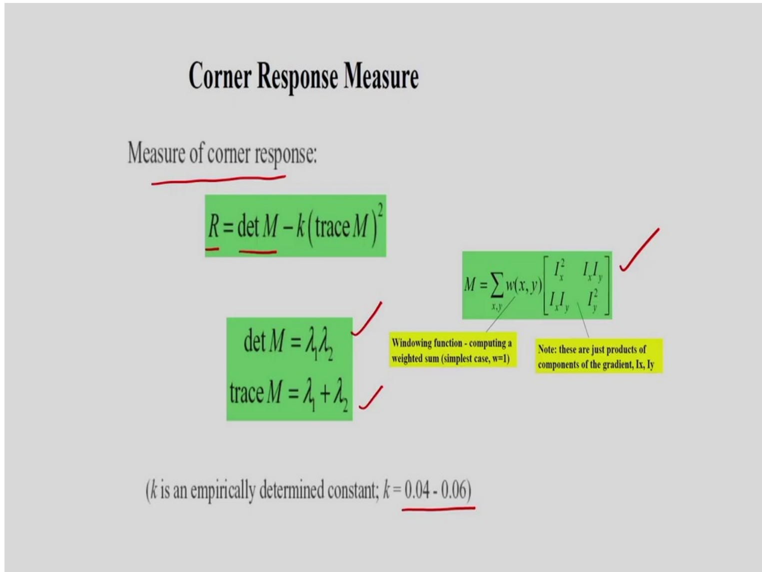

So, for this you can see I can determine the corner response measure with the help of this concept, so how to determine the corner response? The corner response is determined by R that is nothing but the determinant of M, matrix M you can see here, matrix M is nothing but it is computed from the gradient of the image. So, first I have to determine the determinate of M minus k, k is a constant that is the predefined constant and after this I am considering the trace M whole square.

So, what is the determinant of M? Determinant of M is nothing but lambda 1 into lambda 2. And what is the trace of M? The trace of M is lambda 1 plus lambda 2 that is the trace of M. And the value of k is empirically determined it lies between 0.4 to 0.6. And based on this corner response measure that is the R I can detect the corner points.

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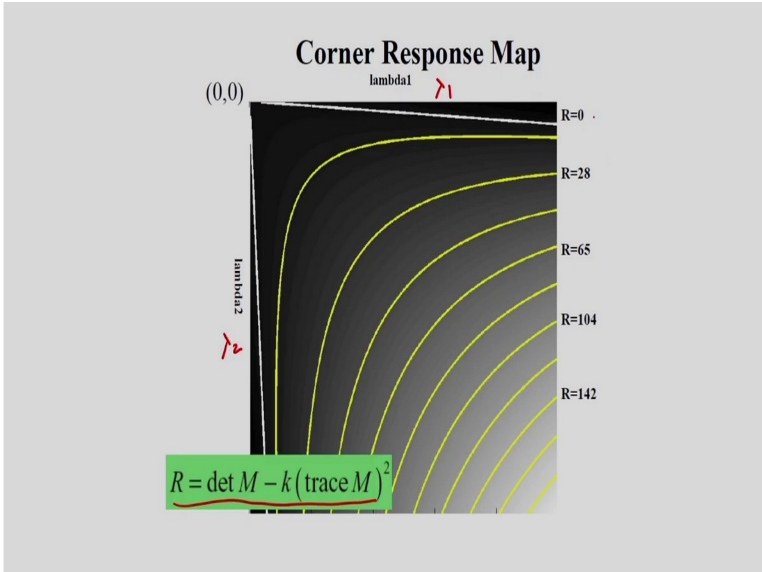

So, here you can see the corner response map and I am considering the lambda 1 in this direction and lambda 2 in this direction and I am determine the response that is mainly from the determinant of M and also from the trace of M and you can see I am showing the responses, response will be 0 response is 28 like this I am considering all the responses the corner response map.

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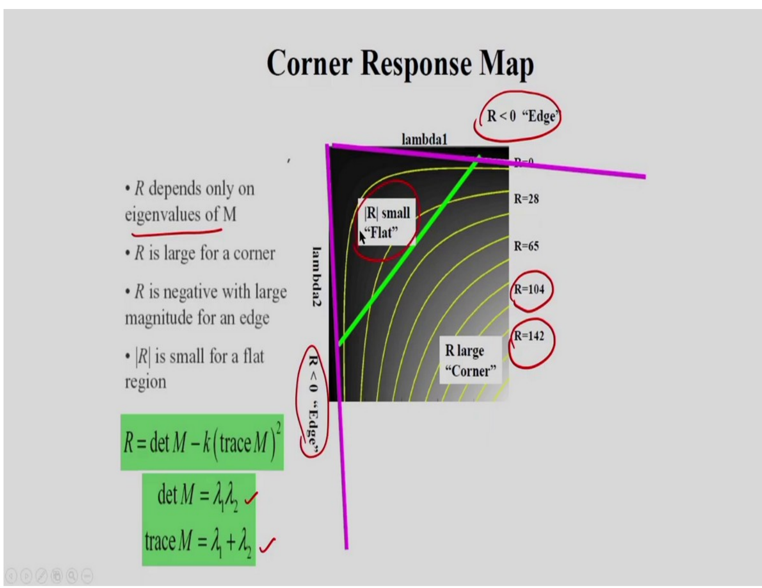

And in this case you can see the R depends on the eigenvalues of M. So, this response depends on the eigenvalues of M, because we have to determine the determinant of M that is nothing but lambda 1 into lambda 2 and also we have to determine the trace of M that is nothing but lambda 1 plus lambda 2. And R is large for a corner, so in this case you can see if I consider this value R is equal to 142 or maybe 104 that corresponds to the corner points.

And R is negative with large magnitude for an edge, so you can see for edge R is negative and also you can see R is negative for the edges. And r is small for a homogeneous for a flat region. So, you can see r is small for a flat or the homogeneous region. So, based on this corner response I can determine the location of the corner points.

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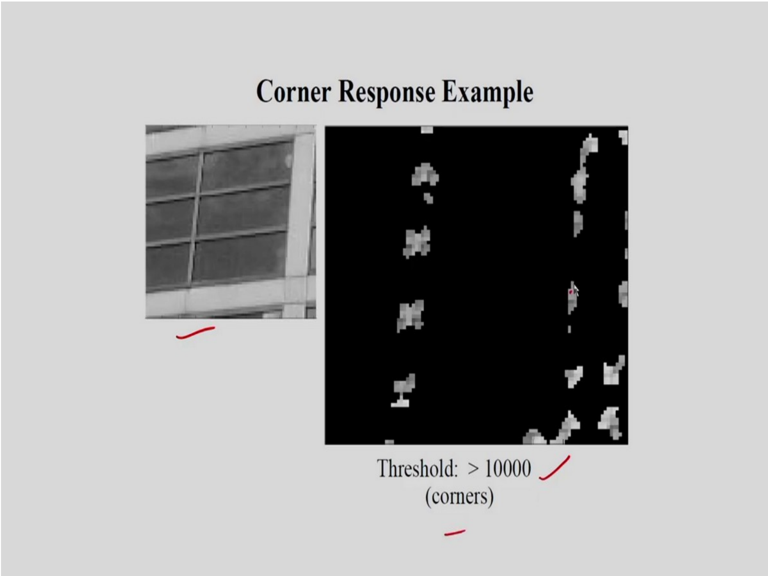

And in this example I have shown the input image and I am considering the threshold the threshold is suppose 10,000 something like this and based on this I am determining the corner points, with the help of the Harris corner detector.

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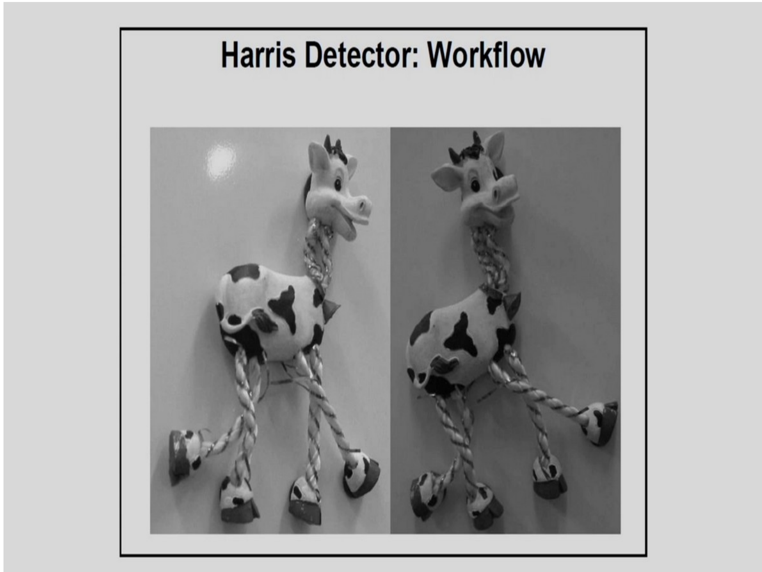

And in this case what I am considering? Two images I am considering and I am considering the affine transformation and also the photometric variations. In this case also I have to determine the corner points, because it should be invariant to affine transformation and the photometric variations.

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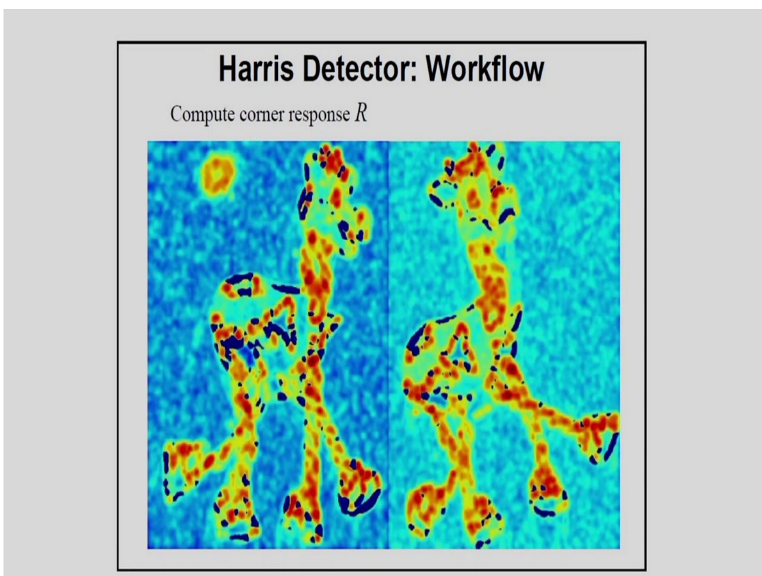

So, here you can see based on the corner response R, I am determining the corner points, for the both the images.

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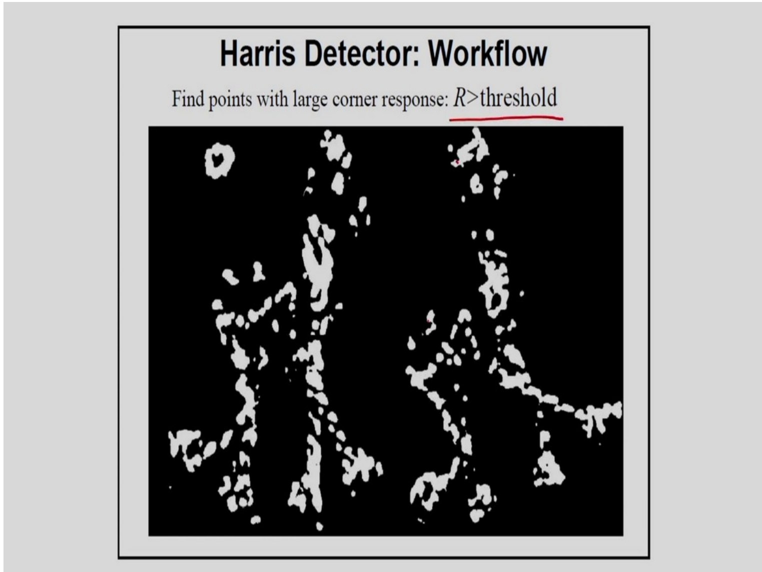

And also you can see if I consider the response is greater than a particular threshold and corresponding to this I am determining the corner points. So, all the corner points I am determining.

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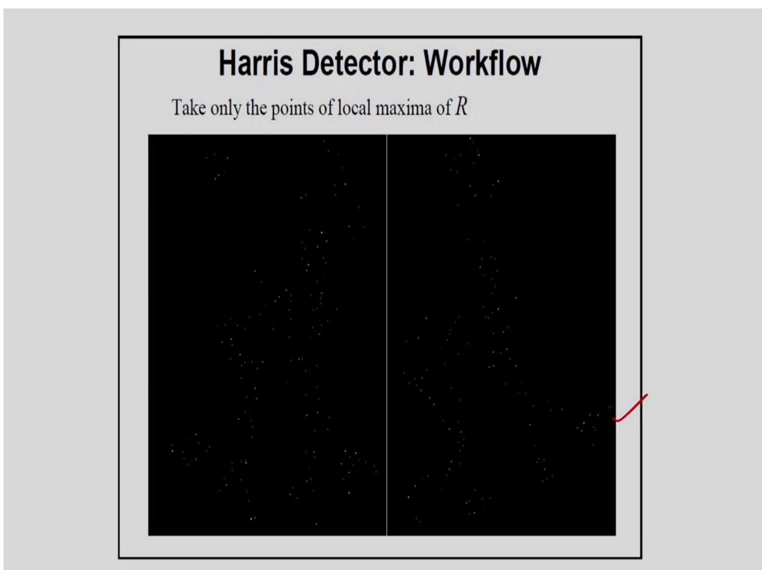

And if I consider take only the points of local maximum of R and corresponding to this you can find the corner points for the both the images you can find. So, like this I have to determine the corner points.

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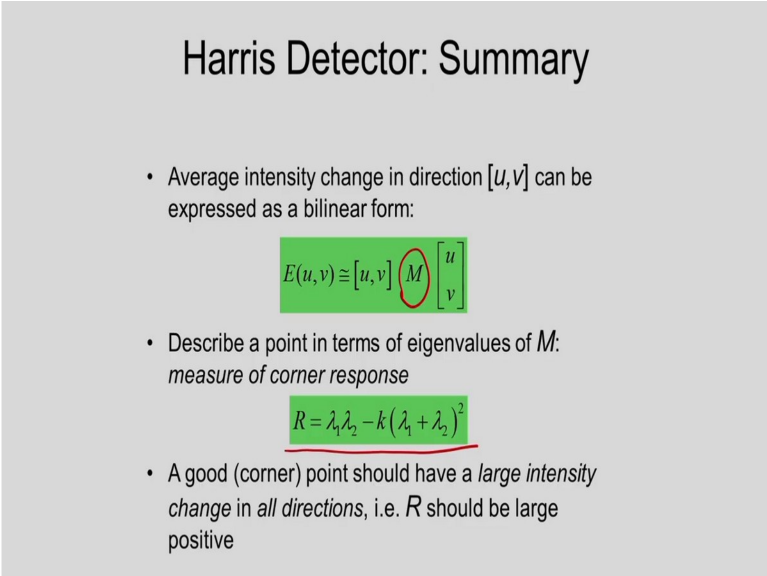

So, the Harris corner detector the summary is I have to determine the matrix M that is important, so matrix M I can compute from the image gradients. And from the matrix I can determine the corner response, the corner response is nothing but lambda 1 into lambda 2 minus k lambda 1 plus lambda 2 whole square that is the corner response. So, that means lambda 1 and lambda 2 are the eigenvalues of the matrix M.

So, matrix M is I am considering and corresponding to the matrix M I am determining the eigenvalues. So, eigenvalues are lambda 1 and lambda 2. And in the pictorially what is the meaning of the lambda 1 and the lambda 2, lambda 1 is nothing but that is the corresponding to the major axis of the ellipse that is the eigenvalue and corresponding to the minor axis the eigenvalue is lambda 2. But from the matrix M I have to determine the eigenvalues lambda 1 and the lambda 2. And after this based on this corner response I can determine the corner points.

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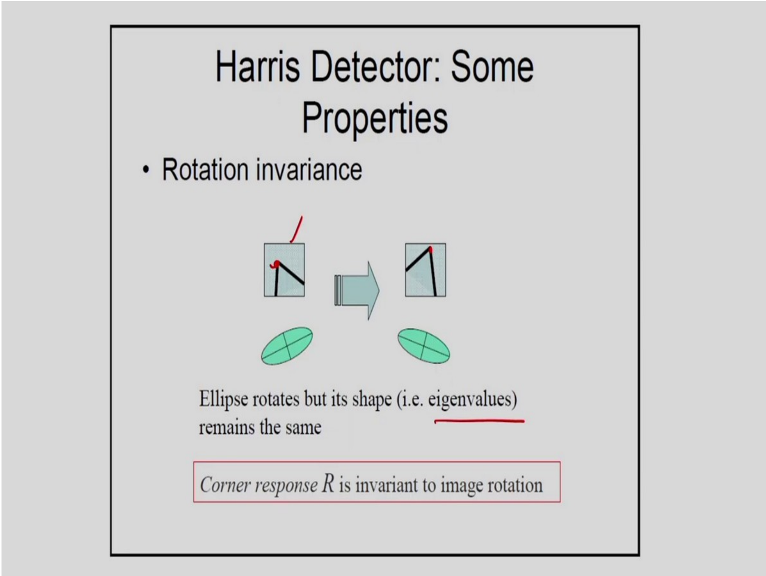

And for a Harris detector some properties I have to explain, the first property is the rotation invariant and in this case you can see one corner I am considering you can see one corner I am considering and it is rotated then in this case the ellipse rotate but its shapes remains the same that means the eigenvalues will remain the same.

So, that means the corner response R is invariant to image rotation in case of the Harris corner detector. So, this example I have shown that corner point is rotated but what is happening the eigenvalues remains the same in both the cases and that is why the corner response R is invariant to image rotation.

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And this concept already I have explained what is the meaning of the covariance and the invariance, so what is invariance? Suppose the image transformed and the corner locations do not change that is nothing but invariance and if we have two test from versions of the same image, that means I am doing some affine transformation of an image and feature should be detected in the corresponding locations.

So, in the corresponding locations the feature should be detected, here you can see I am determining the corner points or the interest points and in this case I am considering affine transformation that is I may considered rotation translation scaling like this and also I am considering photometric variations. So, this concept is quite important.

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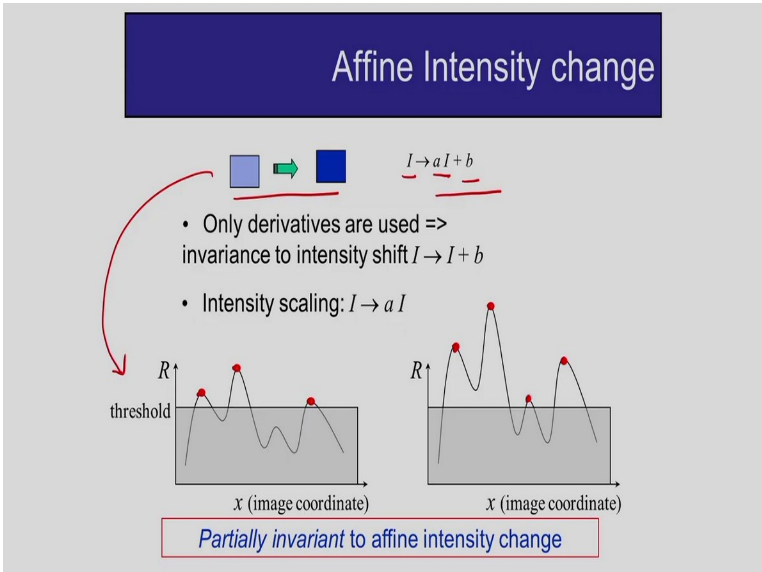

So, in this case I am showing one case that is the affine intensity change. So, I am showing these two images and the intensity is change. So, for this I am considering I is the intensity of the original image and after this I am doing the intensity scaling the intensity scale a into I and I am considering the offset, the offset is supposed to b.

And corresponding to the first image there intensity is I and if I apply the gradient operation so gradient operation you can see in the gradient operation I have to determine the maximum value, so the maximum of this I have to determine and you can see I am getting the maximum value here the that is a maximum of the gradients.

So, that means I have to find the maximum value that means I am determining the gradients. In the second case what I am considering the intensity skill, so the intensity is increased and again I am applying the gradient operation. In this case also I can determine these points the maximum point I can determine, but again you can see I am getting one false positive. So, that is why I can say that is it is partially invariant to affine intensity change that I can I want to explain this concept that is it is partially invariant to affine intensity change.

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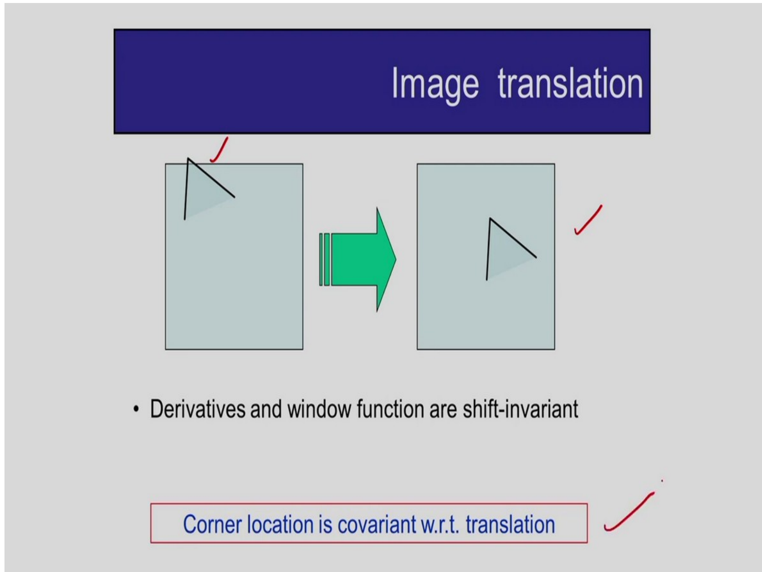

Now, if I consider the translation operation, I am considering one corner point you can see one corner point I am considering and I am doing the translation image translation and in this case I am applying the derivatives and mainly I am considering the window function on window function I am considering and also I am considering the gradient operation that is these are shift invariant the gradient and the window functions are shift invariant, so that is why the corner location is covariant which respect to translation operation that is about the translation.

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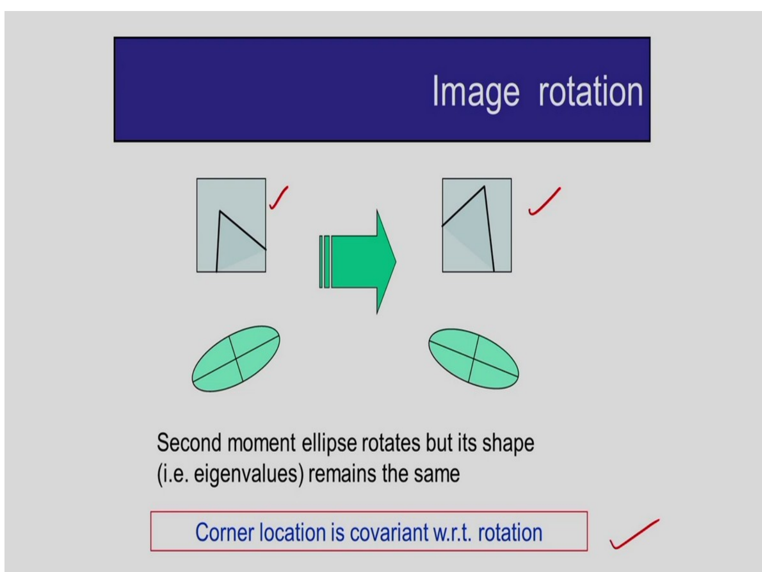

And if I consider the rotation at that concept already I have explained the corner point is rotated this is in the first image in a second image it is rotated, what is happening the ellipse will be rotated but its shapes remains the same that means the eigenvalues remains the same, so that is why the corner location is covariant which respect to rotation. So, we have discussed about the translation and also the rotation let us see about the scaling.

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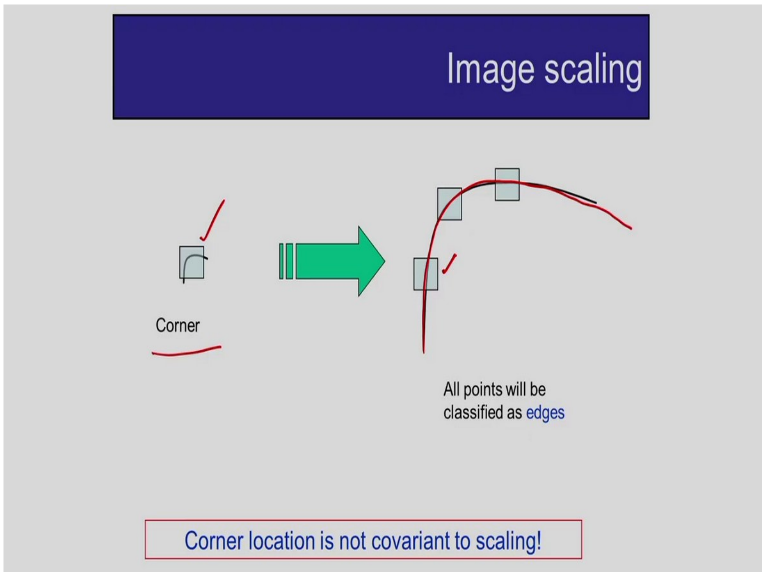

So, I am considering one corner point and I am doing the scaling and in this case you can see if I consider this window function and it is moving, so that we can determine the change in the brightness the change in the intensity then in this case based on the Harris corner detector algorithm, so all the points will be classified as edges.

So, that means the corner location is not covariant to scaling. So, I am explaining this I am considering one corner and after this I am doing the scaling after scaling I am having this is you can see and I am considering the one window function and in this case if I apply this window function and if I consider the Harris corner detector principle, then what will happen in this case? So, all the points will be classified as edges. So, that is why corner location is not covariant to scaling.

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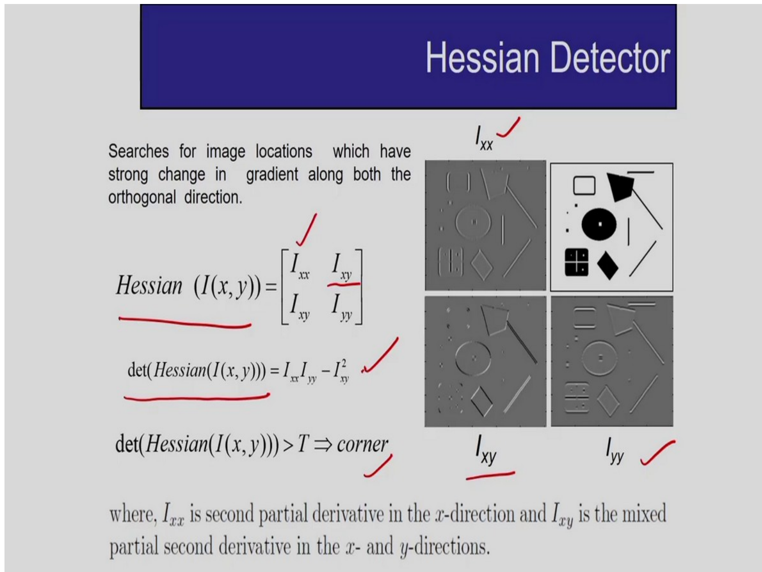

And finally I want to discuss about another detector that is the Hessian detector. So, the concept is very similar, so searches for image locations which have strong changes in gradient along both the orthogonal directions. So, for this also I have to determine the image gradients and I have to determine the Hessian matrix corresponding to the image the image is I x y.

So, you can see first I have to determine Ixx, what is Ixx? Ixx is the second partial derivative in the x-direction. And what is Iyy? Iyy is the second partial derivative in the y direction. And also I have to determine I x y I have to determine that is I x y is the mix partial second derivative in the x and y directions. So, I have to determine all these derivatives.

So, I have to determine Ixx, I have to determine Iyy and also I have to determine the mixed partial second order derivative I have to determine. And from this I have to determine the Hessian matrix. So, you can see I am determining the determinant of the Hessian matrix that is nothing but Ixx into Iyy minus I x y whole square. So, I am determining the determinant of the Hessian matrix. And if the determinate of this is greater than a particular threshold then the corner points will be detected. So, this is the main concept of the Hessian detector Hessian corner detector.

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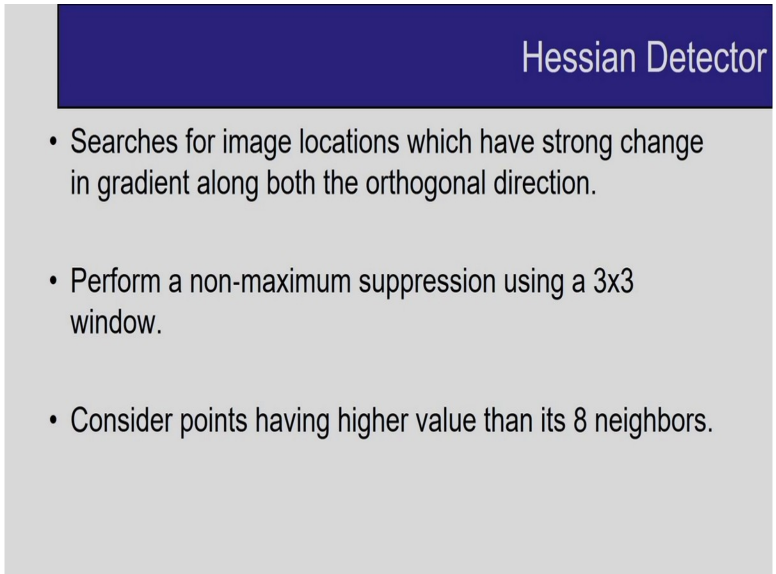

So, in this case searches for image location which have strong change in gradient along both the orthogonal directions and also we have to perform a non-maximum suppression using a 3 by 3 window that is also very important, so I have to perform a non-maximum separation using a 3 by 3 window and also we have to consider points having higher value then it's 8 neighbourhood that is we have to consider and based on this we can eliminate false corner points. So, this is about the Hessian detectors.

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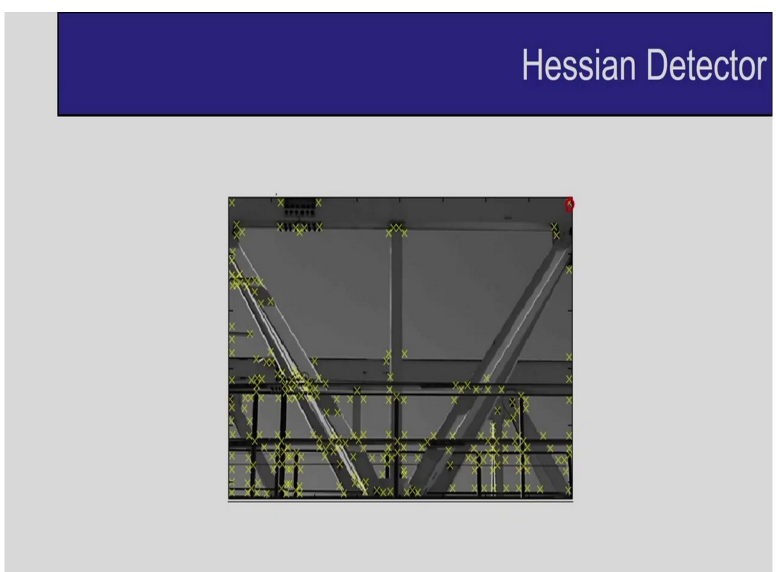

And you can see I can determine the corner points with the help of this algorithms, this is the Hessian detectors to detect the corner points, you can see all the corner points. So, in this class I discussed the concept of the interest points and the interest points should be robust to affine transformation and also the photometric variations and with the interest points, I can do image matching, so I had given some examples, one is the stereo correspondence, I can find a stereo correspondence between left image and the right image.

Also, I have given another applications that is image stitching for image stitching also I have to do image matching with the help of the interest points. And I have discussed one important corner detector that is the Harris corner detector. So, let me stop here today. Thank you.