Computer Vision and Image Processing - Fundamentals and Applications

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Lecture-24

Image Texture Analysis - I

Welcome to NPTEL MOOCs course on Computer Vision and Image Processing Fundamentals and Applications. Today I am going to discuss about image texture analysis. So, what is image texture? Image texture means spatial distribution of gray level intensity values, that is how the gray level intensity values are distributed spatially, that is the definition of image texture. The basic element of a texture is called Texel. Texel means a group of pixels having homogeneous property, that is the definition of Texel.

And Texel is repeated spatially and we get a particular texture. Texture is a very important image feature. Human can distinguish different surfaces based on texture. So, in computer vision also, the texture is a very important image feature. The texture feature can be combined with other features like color feature, motion feature, shape features for object recognition for image classification. And for texture analysis, there are actually many approaches we will discuss all these approaches.

And there are mainly 4 research directions, one direction is texture classification. So, texture classification means we have to extract texture features and based on these texture features, we can classify different types of textures present in an image, that is called texture classification. And another direction is the texture segmentation. So, based on texture information, we can do image segmentation. Image segmentation means partitioning of an image into connected homogeneous region.

So, by considering the texture information, we can do the image segmentation. Another direction is texture synthesis. So, from a small texture, I can generate a big texture. So, the input is a small texture and from that texture I want to generate a big texture of an image. Another direction is the already I have explained in my first class, shape from texture. That is the shape I can determine from texture variations. Texture variations give you to estimate the shape of a particular surface.

So, these are main research directions, one is texture classification, one is texture segmentation, one is texture synthesis, and one is shaped from texture. So, now, I will discuss about the concept of texture analysis and I will discuss the texture synthesis also.

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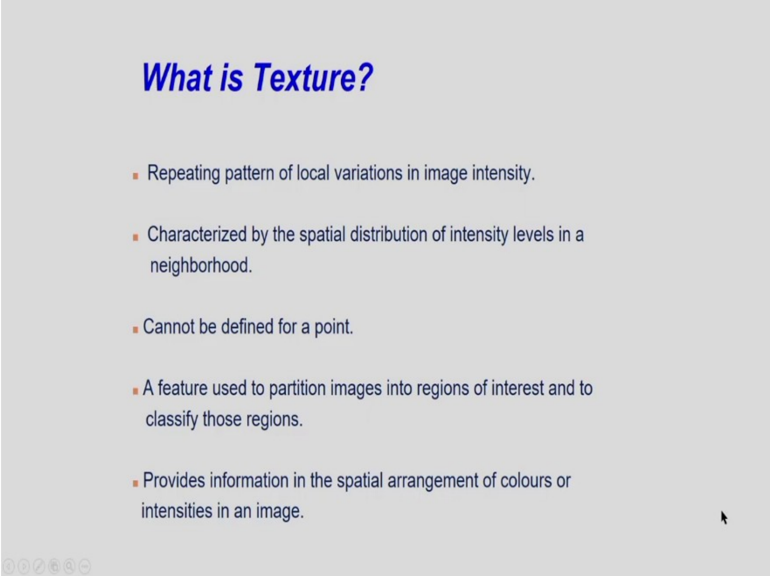

So, here you see the definition of a texture, a repeating pattern of local variations in image intensity, that is spatial variation in image intensity that I am considering. It is characterized by the spatial distribution of intensity levels in a neighborhood and the texture cannot be defined for a point. A feature used to partition image into regions of interest and to classify those regions, that is, I can use the texture features. And the texture provides information on in the spatial arrangement of color or intensities in an image. So, this is the definition of a texture.

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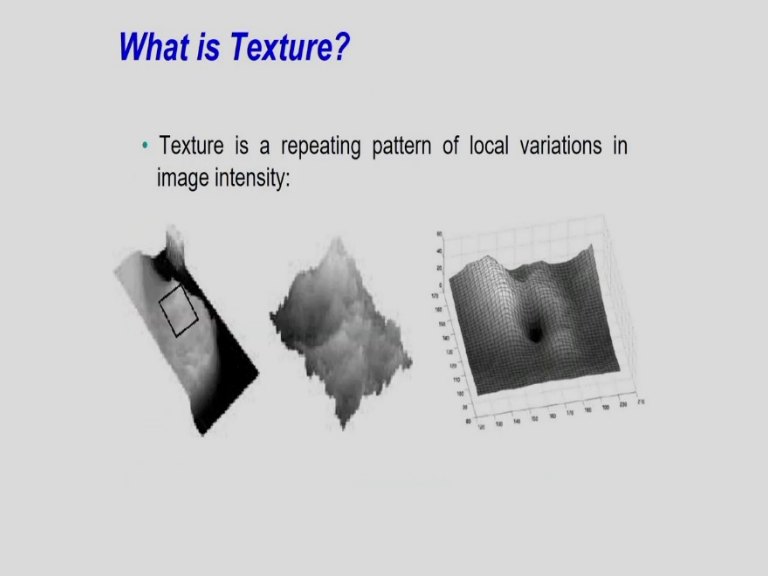

And in this example, in this figure you can see, a texture is a repeating pattern of local variations in image intensity, you can see the texture and you can see also the local variations in image intensity. So, you can see this portion of the texture and corresponding to that portion you can see local variations in image intensity.

So, you can see the image intensity these variations in this case. And in this figure also I have shown a particular texture. So, from this you can see the shape of a particular surface can be estimated from the information of texture variations. That concept already I have explained in my first class.

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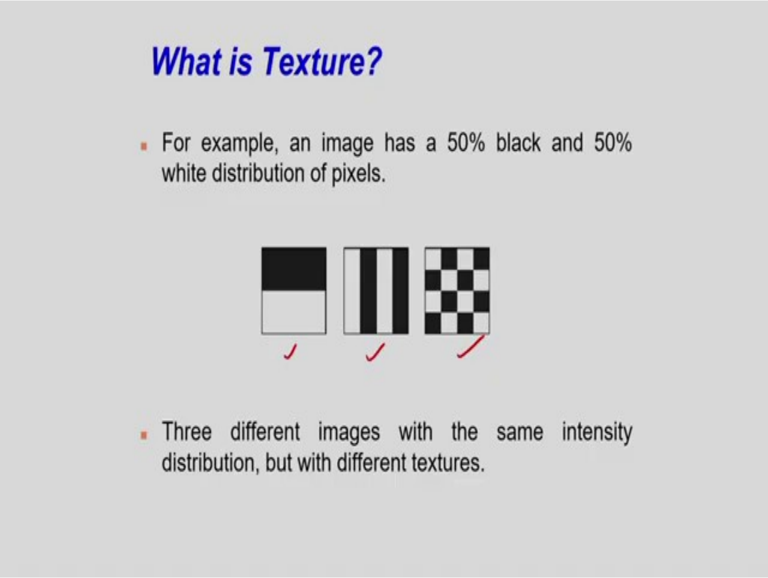

So, in this case as you can see, in this example, an image has 50 percent black and 50 percent white distribution of pixels. And corresponding to this case, I may have three different images with the same intensity distribution, but in this case the different textures. So, in this case, you can see I have the first texture, second texture, third texture and in this case, you can see the 50 percent black and the 50 percent white distribution, but, the different images I am getting.

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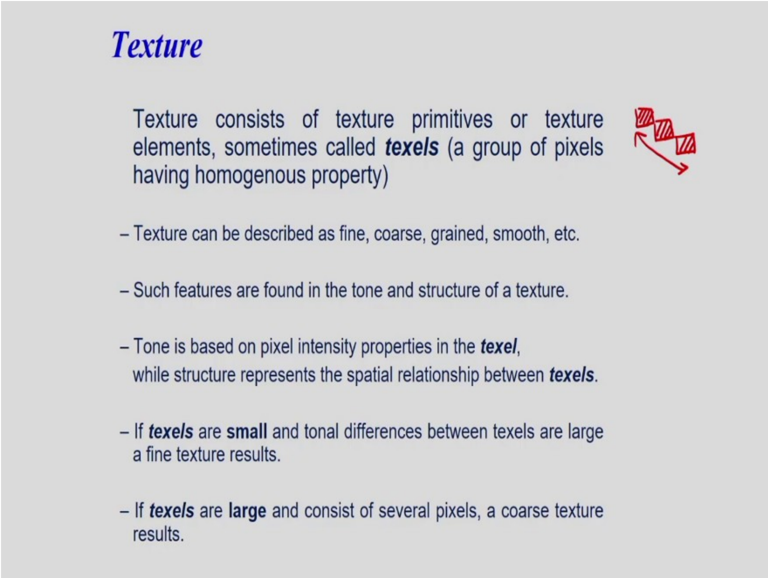

And texture consists of the texture primitives. The texture primitive is called the Texels. So, what is the definition of texels? A group of pixels having homogeneous property that is called the Texels. So, if I consider a particular texel suppose, a group of pixels having homogeneous property, so, this Texel is spatially distributed, suppose, suppose this distributed I am considering and I will be getting a texture.

And in this case the texture can be described as the fine texture, the coarse texture, the grain texture and the smooth textures. Such pieces are found in the tone and the structure of textures, because the textures are mainly the fine textures, the coarse textures, the grain textures and the smooth textures.

So, what is the definition of the tone? The tone is based on pixel intensity properties in the Texel. And what is the meaning of the structure? The structure represents the spatial relationship between the texels. So, in this case, you can see, I have shown one spatial relationship and that is called the structural property, the structure of the texture. If Texels are small and the tonal differences between texels are large, then corresponding to this I will be getting a fine texture.

And also, if the pixels are large and consist of several pixels, then I will be getting a coarse texture. So, mainly you can see that based on the pixels, I can define the different types of textures, the fine textures, course textures, grain textures and smooth textures.

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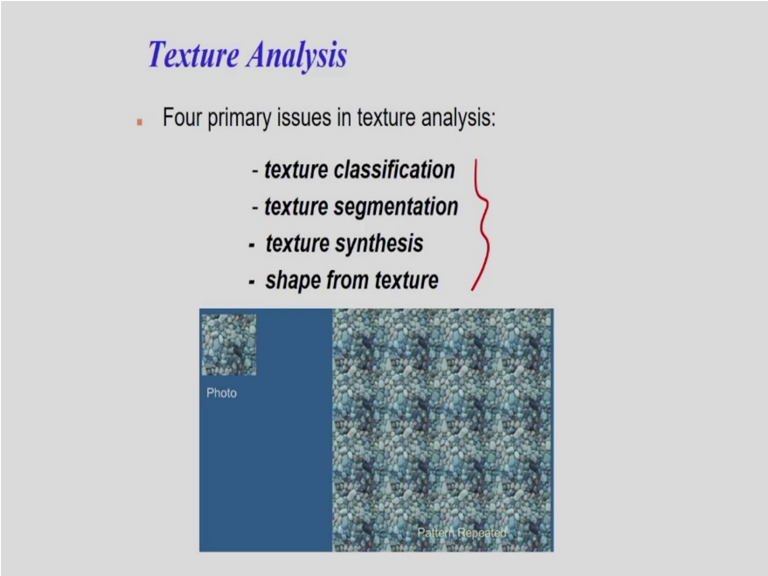

So, already I have defined that is there are 4 primary issues in texture analysis, one is the texture classification, one is texture segmentation, one is texture synthesis, and another one is the shape from textures. So, we can consider these research directions in computer vision. So, here you can see this photo, if I consider this photo and the photo is repeated this pattern is repeated and I am getting the textured image.

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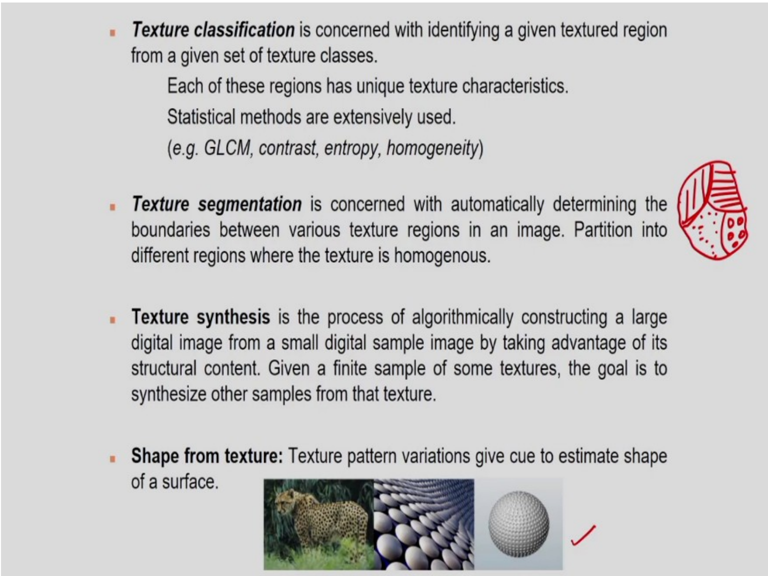

So, what is texture classification? Texture classification is concerned with identifying a given textured region from a given set of texture classes. So, I have texture classes and in this case I have to identify a textured, given textured region, that is the texture classification. So, for this I have to extract texture features, maybe I can extract some statistical features like GLCM.

GLCM is called the gray level co-occurrence matrix, some texture statistical parameters like contrasts, entropy, homogeneity. So, these features I can extract and based on these features, I can do the texture classification.

Another one is the texture segmentation; the texture segmentation is the partition into different regions. Suppose if I have an image so, I have to partition into different regions where the texture is homogeneous. So, suppose if I consider one image suppose one region and suppose these are different types of textures. So, I am just partitioning the image based on the textures. So, this is one kind of texture and this is another kind of texture, this is another kind of textures like this and suppose this is another kind of textures.

So, that is I am doing the partitioning into different regions where the texture is homogeneous. So, corresponding to this region, suppose that corresponding to this region that texture is homogeneous, that I am doing. So, that is based on the texture, I am doing the image segmentation. The next one is the texture synthesis. The texture synthesis means, I have to construct a large digital image from a small digital sample image. That is, I can generate a large digital image from a small texture, that is the concept of the texture synthesis.

So, the goal is to synthesize other samples from that particular texture. So, I can generate other textures or maybe I can generate a large digital image from a small texture pattern, that is called texture synthesis. And shape from texture is that texture pattern variations give cue to estimate shape of a surface. So, in this case you can see these examples, you can see the texture pattern variations and this texture pattern variations indirectly give some information to estimate shape of a surface.

So, this is called shape from texture. So, I will discuss all these concepts one by one, one is the texture classification for this I have to extract texture features. For texture segmentation also, I have to extract the features, that is called texture segmentation. For texture synthesis, from a small texture how to construct a large digital image, that I can show some examples. And one concept is the shape from texture.

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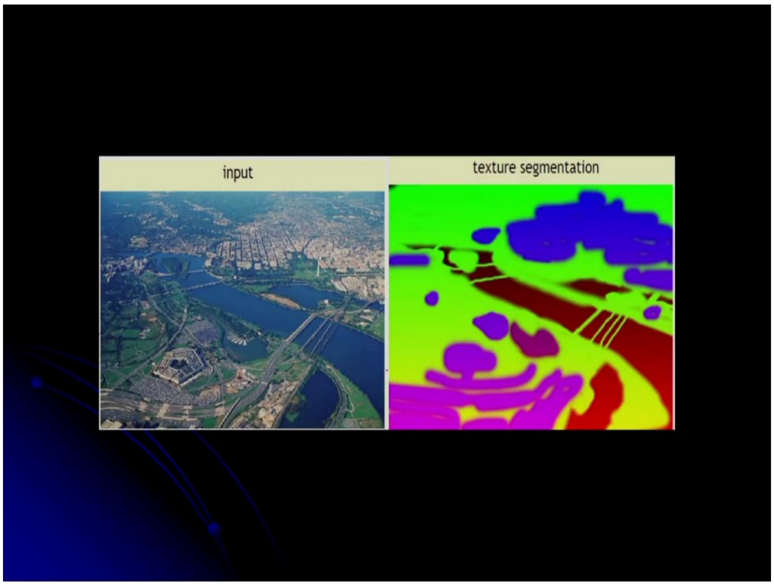

This is one example of image segmentation based on textures. So, in the left you can see the input image and in the right, you can see the segmented image and it is based on texture information.

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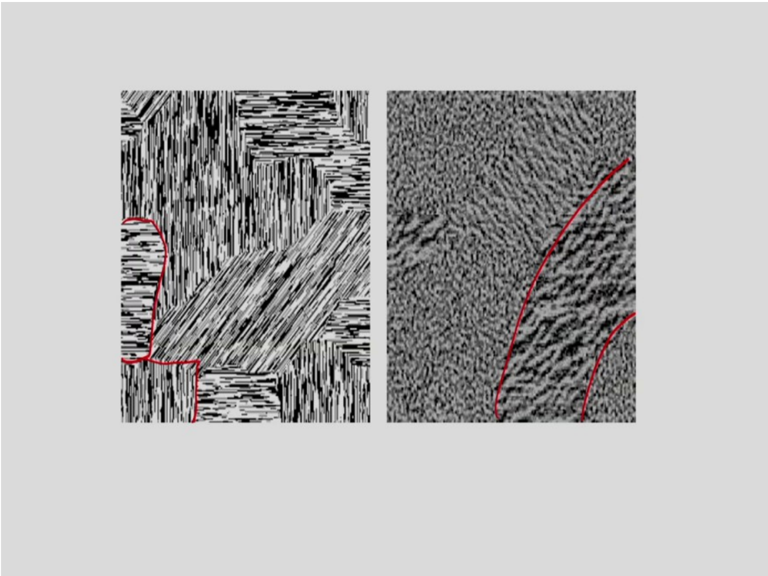

And similarly, you can see these two images. So, based on the textures, we can segment out at different regions of an image. So, I can do the partitioning. So, suppose corresponding to this portion, the texture is homogeneous and corresponding to suppose this portion if I consider, the texture is homogeneous.

So, based on this I can do the partitioning of an image. And if I consider the second image corresponding to suppose this portion, the texture is homogenous. So, based on this the texture information I can do the segmentation, the image segmentation.

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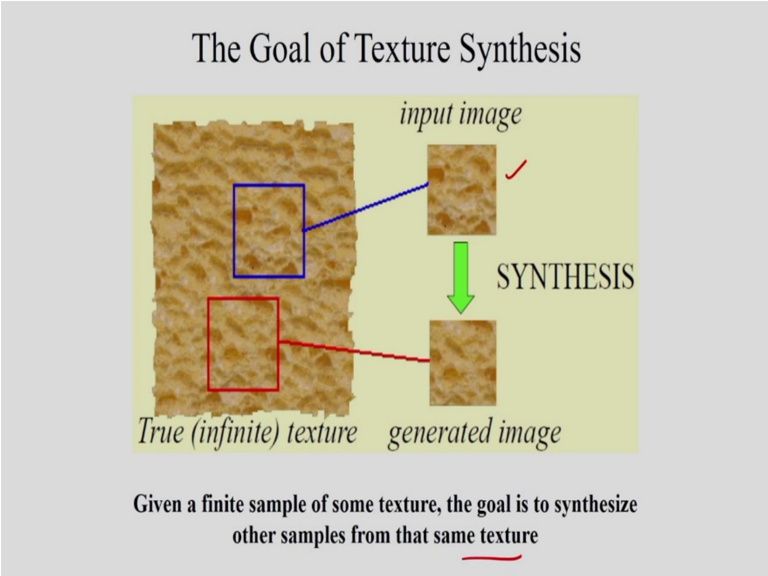

Next one is the texture synthesis. So, for this I have small input image, from the small input image I want to generate the large image based on this texture pattern. So, in this case you can see I can generate images that, you can see the small input image the particular texture pattern I am considering and after this, by synthesis that is artificially I can generate a big image. The goal is to synthesize other samples from the same texture. So, texture is the input texture is given and from this I can generate other samples from that texture, particular texture. So, I can generate a big image. So, I can give some examples of texture synthesis.

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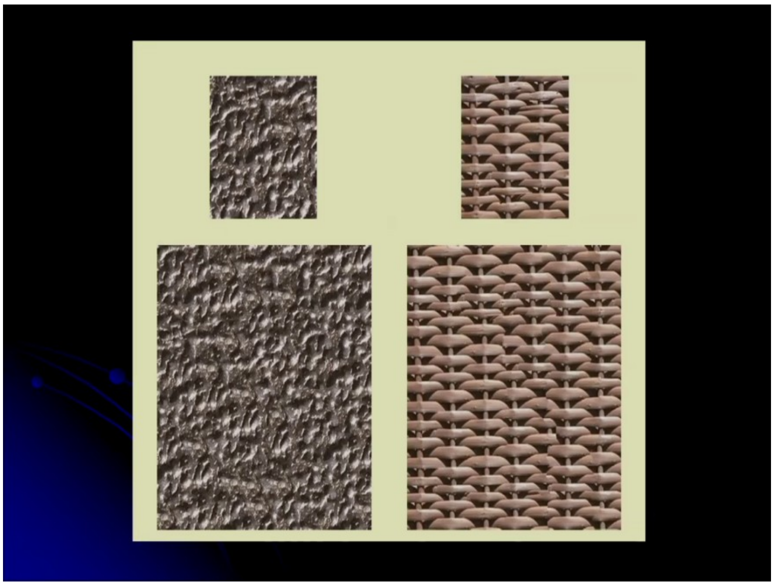

So, here you can see the examples like this. I am considering a small texture pattern and from this I am generating a big image. The texture pattern is repetitive and from this I am getting the bigger images. So, these are the examples of texture synthesis like this I am giving another example, from a small texture pattern I can generate a big image, that is the texture synthesis.

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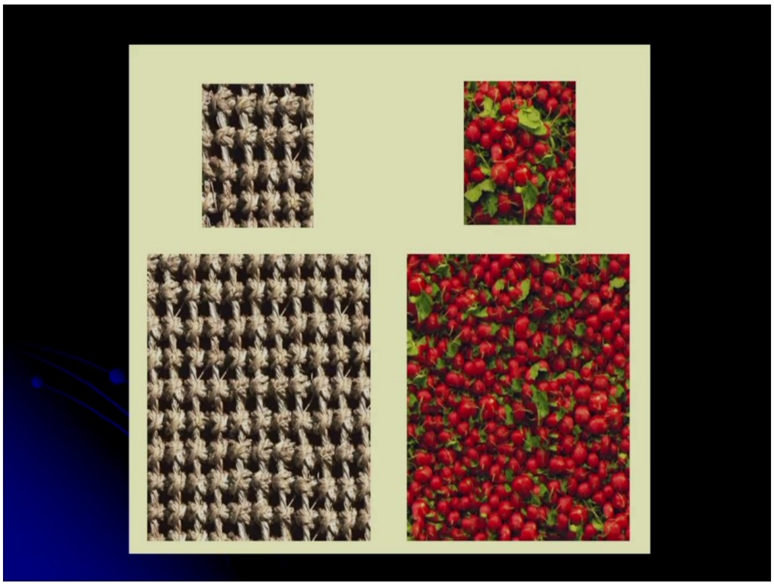

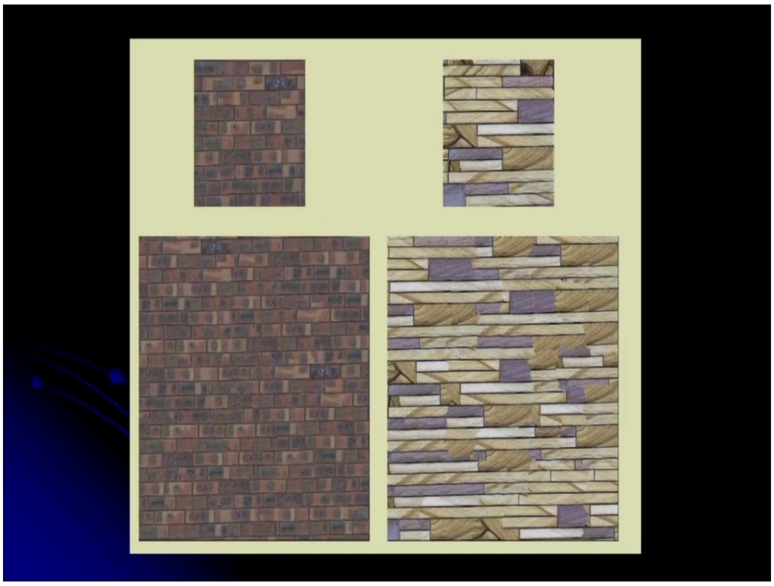

Like this, these are some examples of texture synthesis, you can see this is also another example of texture synthesis.

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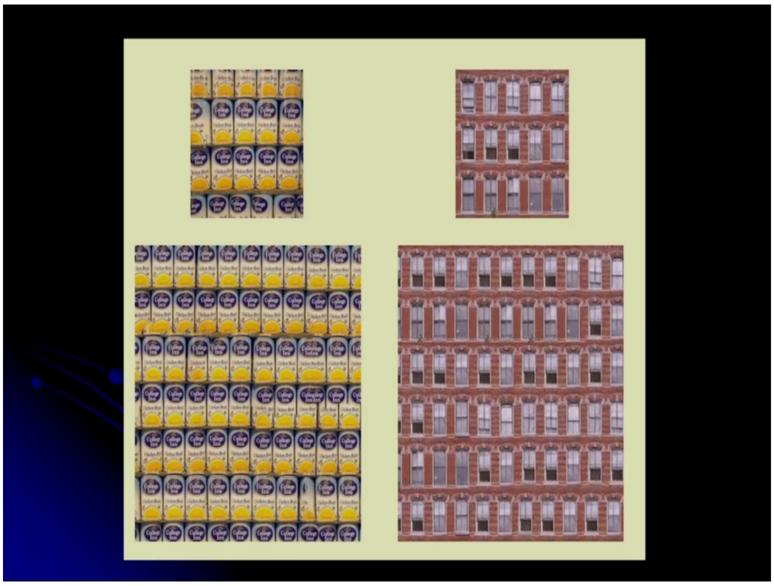

These are again another examples of texture synthesis.

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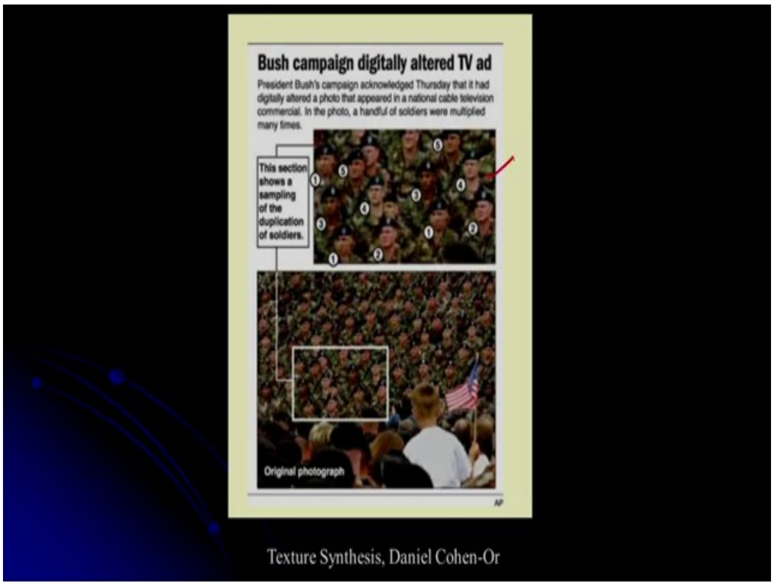

And you can see the texture synthesis sometimes used in image forgery. You can see, this pattern is duplicated, this pattern is duplicated and I am getting this image, the total image I am getting. So, that means the particular texture pattern, this pattern, the first pattern, this pattern is repeated that is duplicated and I am getting the second image. So, that is used for image forgery.

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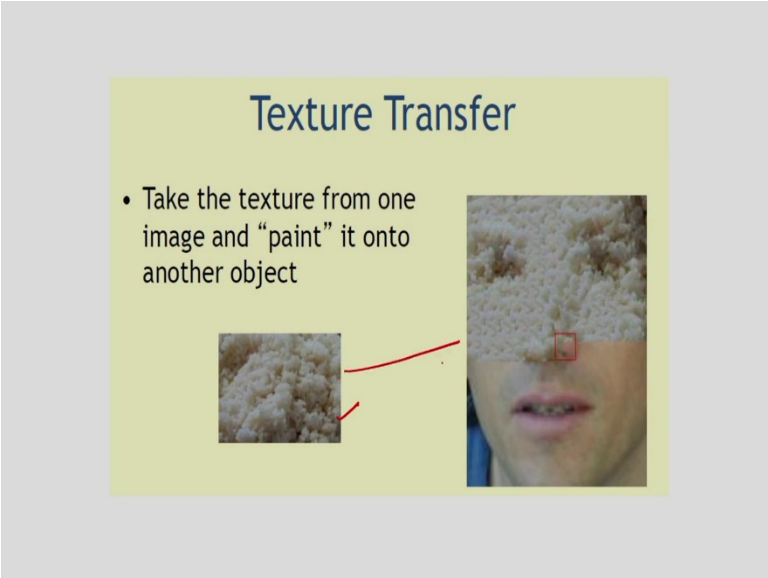

Another research direction is the texture transfer. So, in this case what I am doing, just I am transferring a texture to another image. Take the texture from one image and paint it onto another object. So, that is the concept of texture transfer. So, here you can see that this texture is transferred to that face image. So, this is my face image and that this texture is transferred to the face image.

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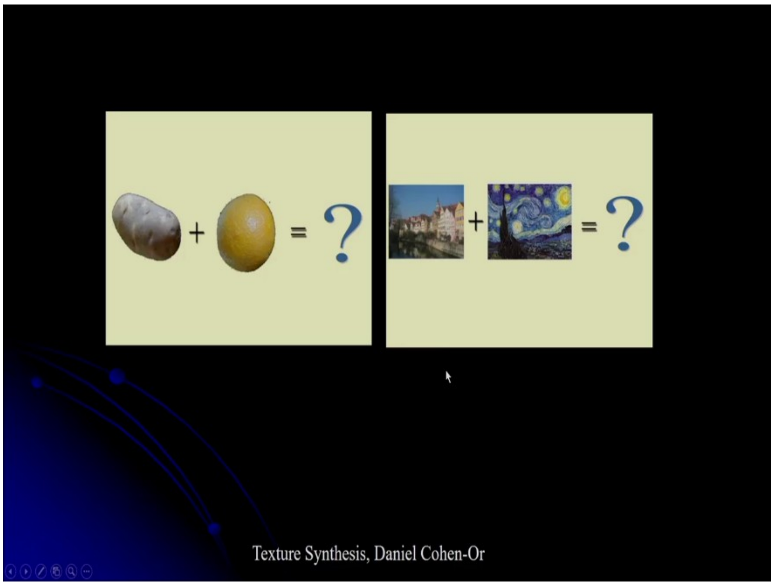

And in this case, this suppose if I consider the first texture in the second texture, so what will be the texture that I can generate from these two textures. Similarly, if I considered this first image and the second image, I can do that texture transfer, the transfer of the texture I can do from these two images.

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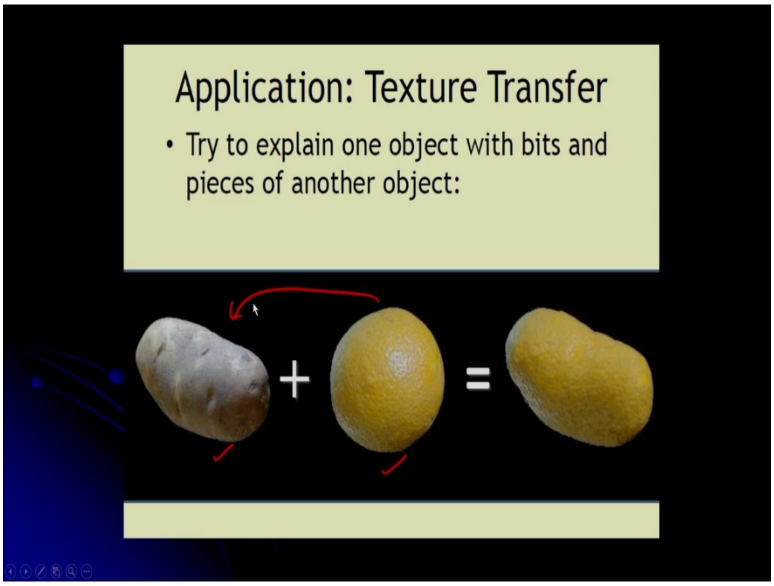

You can see this example, how to do the texture test. The first image you can see the first object and the second image. And I am just transferring the texture to the first object. So that is transferring the texture to the first object, that is the texture transfer.

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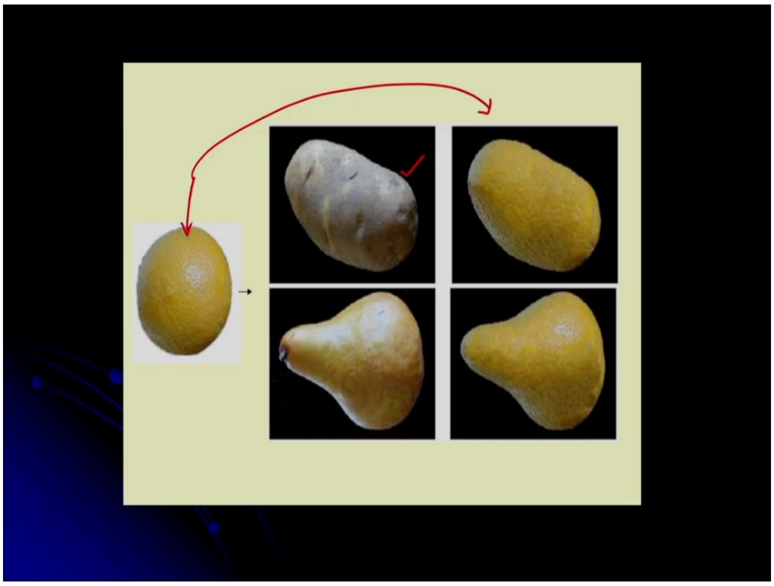

And you can see, just I am transferring the textures to other images. So, this texture, this is the texture and this is transferred to other objects. So, object is suppose this object. So, this is called the texture transfer.

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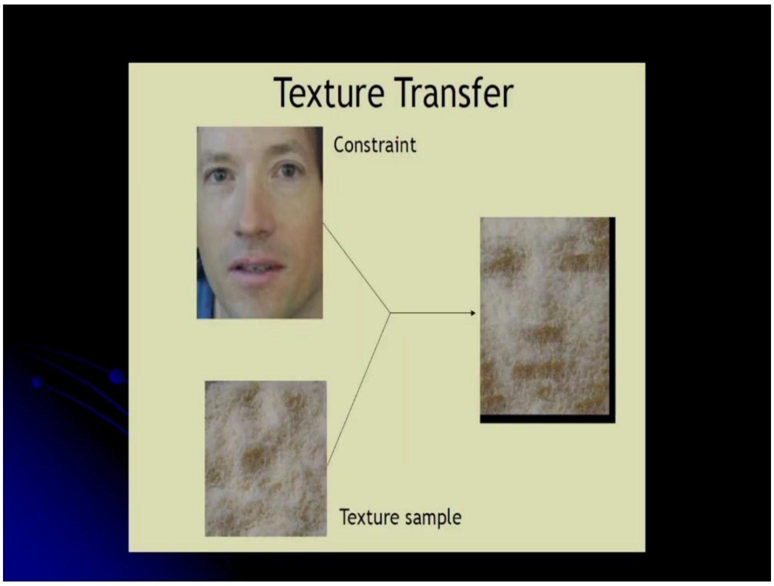

And in this case, you can see the textures transfer I am considering the face image is considered and I am considering the texture sample and that texture sample is transferred to the face image that is that texture transfer.

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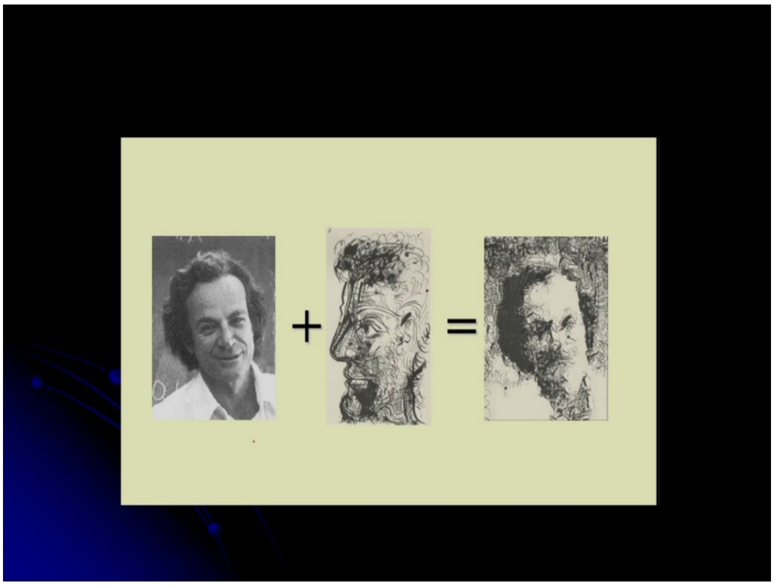

Similarly, I can give another example. This is my input image and I am considering a particular texture and that texture, I am transferring to the face image.

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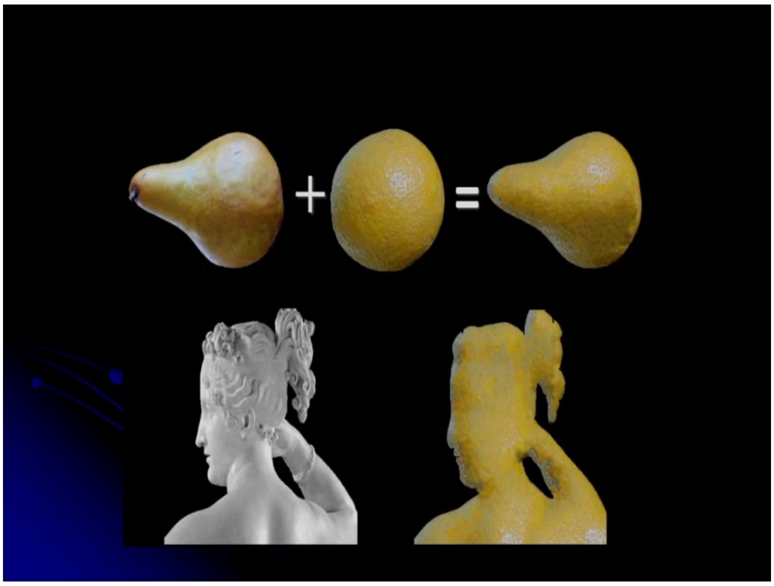

And in this case also I am showing some texture transfer examples. You can see just I am transferring the textures. So, if I consider this object, then this texture is transferred to that object. And similarly, in the second case also, I am doing the texture transferring.

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And this is another example of texture transfer. So, just I am transferring that texture to that face image.

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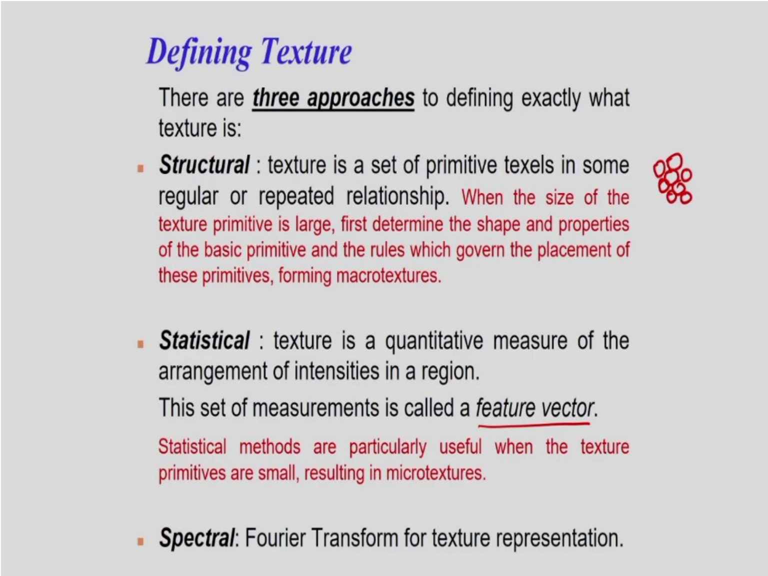

So, this is about the texture transfer. Now, let us discuss how to define a particular texture. So, there are mainly the three approaches, one is the structural approach. In the structural approach a set of primitive texels in a particular spatial relationship is considered and a structural description of the texture is the a description of the Texels and the specification of the spatial relationship. So, because the texture is a set of primitive Texels in some, some regular or repeated relationships, so, that I am considering.

So, that means, a structural description of the texture, is a description of the texels and specification of the spatial relationship, that is the structural representation of a particular texture. So, that means, in this case, I have that Texels, suppose these are the Texels and how these Texels are distributed spatially that information I am considering. Because these Texels are distributed spatially, so that information I am considering to represent a particular texture.

The another important representation is the statistical representation, that is very important. So, what we can do, we can extract some statistical parameters, the statistical quantities to represent a particular texture. So, I will explain what are the parameters we can extract from a particular texture pattern and based on these quantities, based on these parameters, I can recognize a particular texture, I can classify different types of textures or even I can do texture segmentation.

And in this case, I have to extract the feature vector corresponding to the particular texture. So, in the feature vector I can consider the statistical parameters or statistical quantities which I can extract from a particular texture. And a finally another approach is the spectral approach. So, in this case I can apply the Fourier transformation for texture representation. So, I will discuss these techniques, the statistical technique and the spectral technique because they are very important. So, first let us discuss about the statistical techniques.

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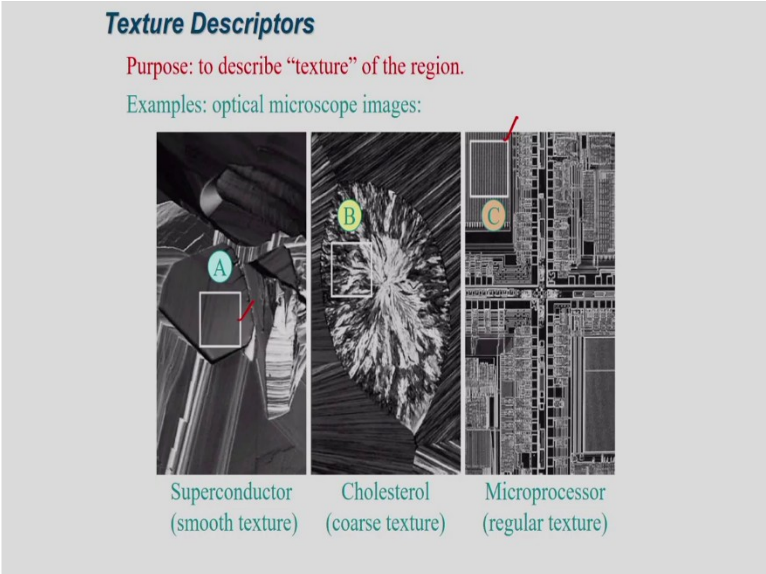

So, in this case you can see I have shown three types of textures. The first one is I am considering a smooth texture corresponding to this portion of the image. Next one is I am considering the coarse texture. And the third one is I am considering the regular texture corresponding to that portion of the image. Now, how to describe a particular texture mathematically?

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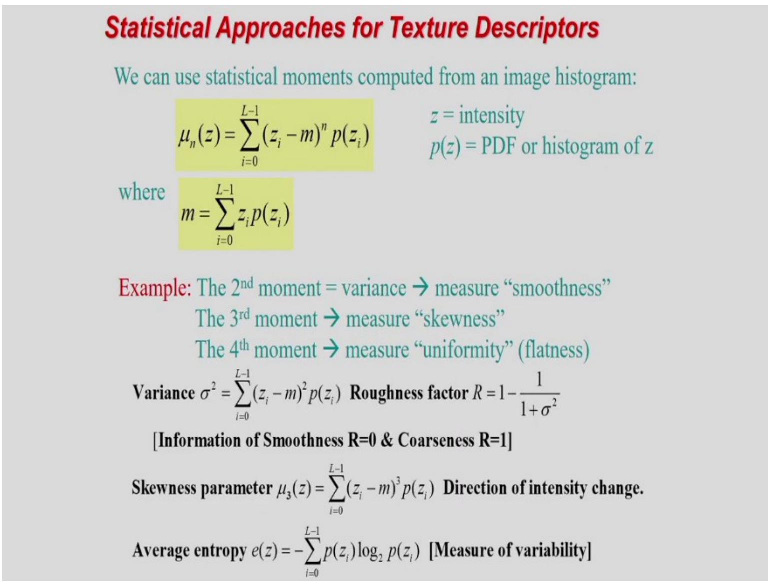

So, for this, the first approach is the statistical approach. I am not going to discuss about the structural approach because nowadays it is not much of use. So, mainly the statistical techniques and the frequency domain technique and these are used for texture representations.

So, for this you can see for statistical approach I can extract statistical moments that I can determine, that I can determine from image histogram. So, in this case I have shown p(z) is the image histogram that is a PDF or the histogram of z, z is the intensity that is the random variable.

And from this you can determine the moments. We can determine the mean, the first one is the mean the mean of the gray levels I can determine. Also, I can determine the second moment that is the variance and it gives the measure of smoothness, the second moment measures smoothness. The third moment also I can determine and this is the measure of skewness, the fourth moment also I can determine and that is the measure of uniformity.

So, you can see I can extract these parameters the second order moment, the third order moment, the fourth order moment I can determine. The second order moment is a measure of smoothness of the texture. The third order moment is a measure of skewness and the fourth order moment is a measure of uniformity. And in this case, you can see I can determine one parameter, one factor that factor is color roughness factor from the variance.

Variance means the second order moment. So, you can see the second order moment is the variance. So, from the variance, I can determine one factor that factor is called the roughness factor. So, based on this roughness factor, I can distinguish two types of textures. Suppose, if R is equal to 0 that corresponds to the smooth texture and if I consider R equal to 1 that means, I will be getting a coarse texture. So, that means, the roughness factors give an information about the smoothness or the coarseness of the texture.

For constant intensity the roughness factor will be 0 and it approaches 1 for large value of variance, that is the concept of the roughness factor. And this skewness parameter that is the third moment I can determine, it gives the direction of intensity sense. And from this I can determine the entropy. Entropy means the randomness, the average entropy I can determine you can see, so, by this formula, I can determine the entropy.

Now, in this representation one problem is, suppose I have one image the image is supposed the spatial distribution of the Texels are like this. So, suppose if I consider digit one image and another image suppose, if I consider in both the cases the image histogram will be same, then in this case by using these parameters, I cannot distinguish these two images. You can see the first image, this is the first image and this is my second image. So, if I want to determine the image histogram, for both the cases the image histogram will be same, the same histograms for these two images. So, that is the problem with this technique.

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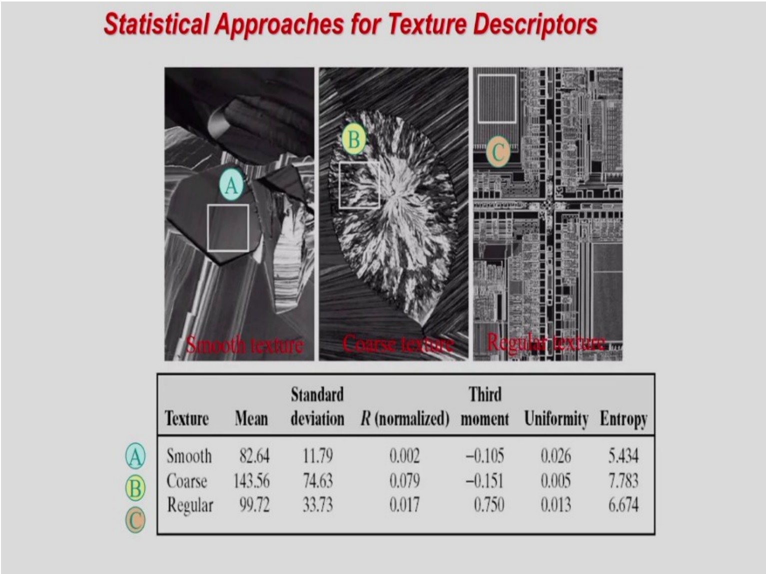

So, in this case, you can see based on these parameters, the mean, standard deviation, roughness factor, third moment, uniformity, entropy, I can distinguish different types of textures. So, you can see I have the smooth textures, the coarse texture and the regular textures. By using this technique, I can distinguish these textures. But one problem already I have explained in the two images, the histogram only be same for both the images.

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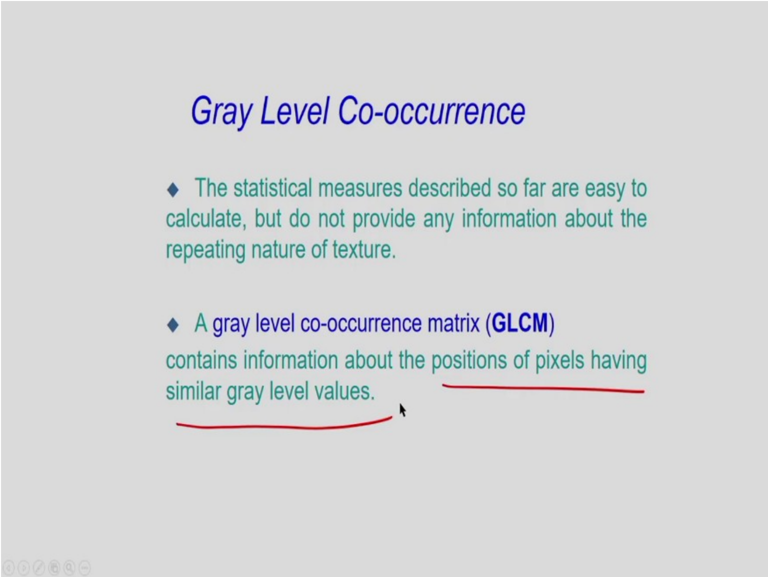

So, for this there is another technique and that technique is I can extract one matrix and that matrix is called the gray level co-occurrence matrix. The statistical measure described so far are easy to calculate, but do not provide any information about the repeating nature of the texture. So that is why I have to consider at this matrix, this matrix is called the gray level co-occurrence matrix that contains information about the position of the pixels having similar gray level values.

So, that information is available in the GLCM, the position of the pixels having similar gray level values. So, now, I will explain how to determine the GLCM matrix, that is a gray level co-occurrence matrix how to develop that I will explain. So, let us consider how to determine the gray level co-occurrence matrix.

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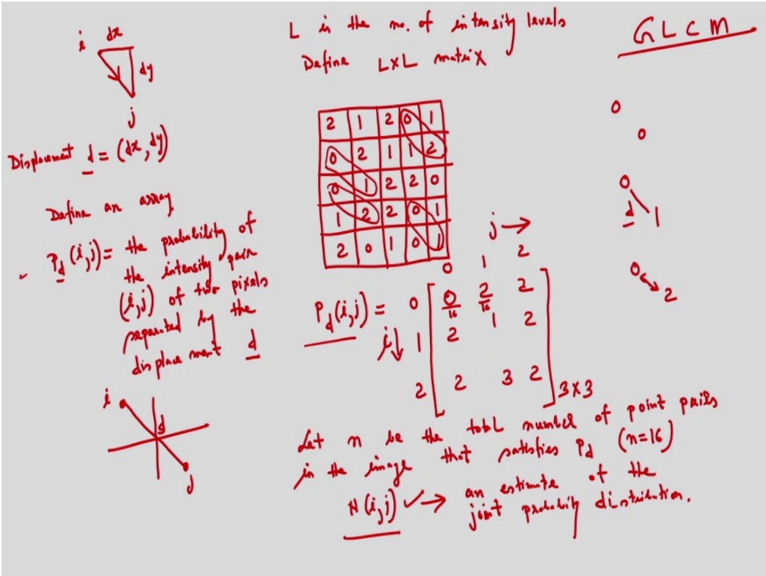

So, let us consider two pixels, one pixel is suppose I and another pixel is j. So, suppose this is dx and this is dy and you can see the displacement between the pixels i and j. So, first I have to define the displacement vector between the pixel i and j. So, that is dx along the x direction and d y along the y direction that is the displacement vector. So, displacement I am considering. After this I have to define an array. So how to define an array, so, I am considering the array is P_d suppose corresponding to the particular displacement P_d (i , j), that array I am considering that is nothing but the probability.

Probability means number of occurrence, probability means number of occurrence of the probability of the intensity pair is i,j of two pixels separated by the displacement vector by the displacement by displacement d. So, that means, in this case I am considering the pixels i and j, this pixel is this pixel is i and this pixel is a and I am considering the displacement is d, d is the displacement between i and j. And in this case how to determine this array, so, the array is the P_d(i,j) So, that is the co-occurrence matrix.

So, suppose L is the number of intensity levels. So, L is the number of intensity levels present in an image. So, for this I have to define L by L matrix L × L matrix, define L by L matrix for individual pairs. So, let us consider one example. Suppose, I am considering one image, suppose it is a 5 by 5 image. So, this 5 by 5 image I am considering. So, suppose the pixel values are like this 2, 1, 2, 0, 1, 0, 2, 1, 1, 2, 0, 1, 2, 2, 0, 1, 2, 2, 0, 1, 2, 0, 1, 0, 1. So, this image I am considering. Now, in this case, so, what will be the size of the co-occurrence matrix.

So, in this case you can see I am considering the gray values, the gray levels 0, 1 and 2. 0, 1, 2 that means, I have three gray values. So, that is why my array size will be P_d (i,j) that is the co-occurrence matrix, the size will be 3 by 3 matrix. Because this is L by L matrix so I am considering only 3 levels. So, that means my size will be 3 by 3 P_d (i,j). So, this side is i, so i is 0, 1, 2 and that side is 0, 1, 2 that is the direction j in this direction is j and this matrix is 3 by 3 matrix, because I am considering 3 levels, so that is way L by L that means, by 3.

Now, you can see first, the first element is the first you can see this side is i. So, first point if you see this element, what do we mean this element. So, i is 0 and j is 0. So, I have to see whether this pair is available in the image or not. That means, considering that particular displacement, whether that pair is, 00 pair is available in the image or not. You can see the 00 pair is not available in the image. So, that means, this entry will be 0.

Next element is you see this next element is equal to 0 and z is equal to 1 that means is 0 and this is 1 corresponding to this displacement, the displacement already I have defined. So, what is the position of the pixel j. This is dx in the x direction and d y along the y direction with respect to the pixel i. So, that means corresponding to that displacement whether 01 pair is available or not that I have to see in the image. So, in this case, you can see the first 01 pixel.

So, this is 01 pixel, this pair is available and another pair I can see here, the another pair is available, only two pairs. So, that means, this entry will be able to. The next one is, the next element if you see that is i is equal to 0 and j is equal to 2. And corresponding to that particular displacement where the that pair is available or not in the image 02. So, how many times it is occurring in the image. So, you can see 02, this is 02 first one is and another one is 02 is this. So, corresponding to this only I have two times it is occurring. So, this value will be 2.

Like this for all the values of i and j you have to determine, so it will be 2, 1, 2, 2, 3, 2 So, this is an array, the array is P_d (i,j). After this I have to do some normalization. So, how to do the normalization. Suppose, let n be the total number of points pixels, point pairs in the image depth that satisfied pd. So, in this example, how many pairs satisfy this condition? So, in this example, n is equal to 16 in this example. So, that means divide each and every element of Pd that array by n to get the matrix N(i,j). So, I will be getting the matrix N(i,j), the final matrix I am getting N(i,j).

So, for this I have to divide each and every element of this P_d (i,j) by 16. So, that means by n So, that means, if you see it is divided by 16 So, all the elements are divided by 16 like this. That is the normalization I have to do. So, divide each and every element of the array is P_d (i,j) by n to get the matrix the matrix is N(i,j). So, I will be getting that one. So, that means N(i,j) is nothing but it is an estimate, it is an estimate of the joint probability distribution. So, what is the procedure I am repeating it again.

So, corresponding to a particular displacement, I have to define an array, the array is P_d (i,j) So, does the array. So, what is the definition of this array, the probability that means the number of occurrence of the intensity pair ij of two pixels separated by the displacement d, the d already I have defined that is the displacement vector and after this I have to consider a matrix the size of the matrix is L cross L, L means, L is the number of intensity levels I have to consider and based on this I have to develop the matrix the matrix is P_d (i,j), that is the co occurrence matrix.

And for this I have to count probability that is the number of occurrence of the intensity pair of the two pixels separated by the displacement d, that I have to count. After this I have to do the normalization. So, for normalization first I have to see the small n. So, n is the total number of point pairs in the image that satisfied Pd. And in this case after this, I have to divide each and every element of the Pd that is an array by n to get the matrix, the matrix is N(i,j). So, that is the co-occurrence matrix that I have to get and it is an estimate of the joint probability distribution.

So, this is the procedure on how to get the GLCM, gray level co-occurrence matrix. And from the gray level co-occurrence matrix I can determine some parameters to describe a particular texture. So, I will explain what are the parameters we can extract from the GLCM.

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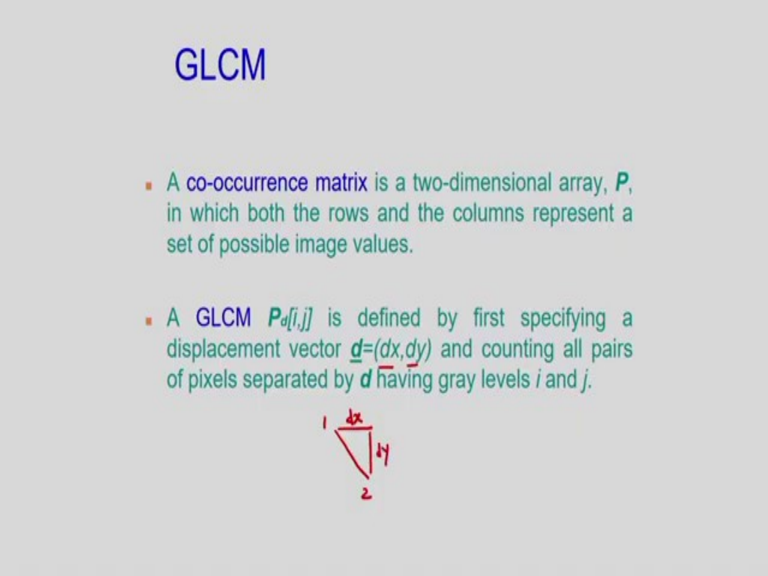

So, a co-occurrence matrix is a two-dimensional array P in which both the rows and the columns represent a set of possible image values, that is already I have explained. And for the GLCM the matrix is Pd is a that is an array I have to define for this I have to first define a displacement vector, the displacement vector is d that is dx along the x direction and d y along the y direction. And counting all pairs of pixels separated by d having gray levels i and j. So, I can determine different, different GLCMs corresponding to different displacement vectors.

In my previous example, I have considered a displacement vector is something like this suppose one pixel is number, one pixel is this number 2 is this, so, it is in the x direction is a dx distance in y direction it is the d y distance. So, this is a displacement vector I can consider.

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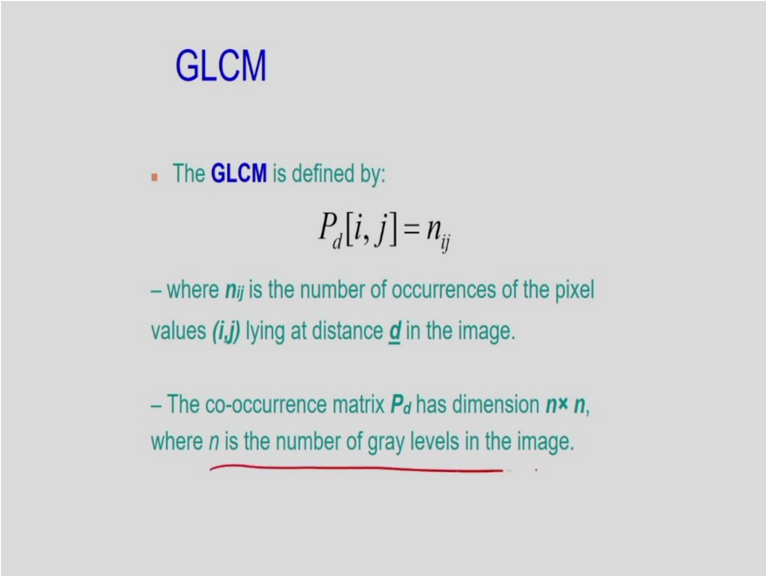

And so, the GLCM is defined by the P_d (i,j) and in this case I have to count, that is the number of occurrences of the pixels value ij lying at the distance d in the image that I have to count. So, where N(i,j) is the number of occurrences of the pixel values i,j lying at distance d in the image. The co-occurrence matrix Pd has dimension n × n, in my example, I have Ll × L, but here I have shown n × n. So, n is the number of gray levels in the image.

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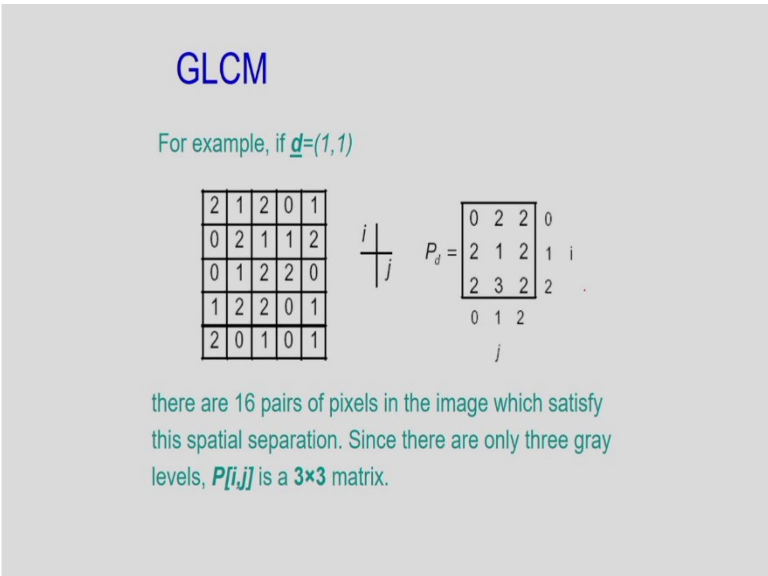

And you can see this example, the same example I have considered corresponding to this particular displacement I can get the array, the array is P_d (i,j) and I have this co-occurrence matrix.

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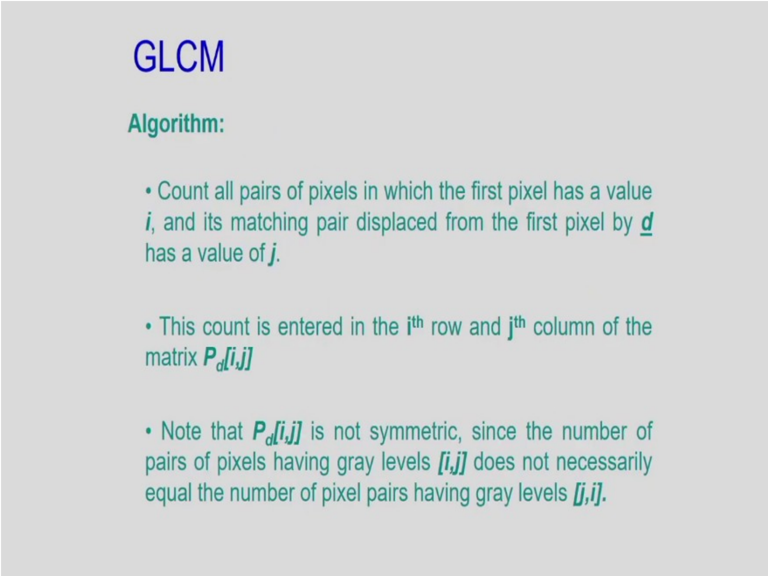

So, algorithm is that, count all pairs of pixels in which the first pixel has a value i and its matching pair displaced from the first pixel by d as the value j, that I have to count. This count is entered in the ith row and jth column of the matrix P_d (i,j), that is the co-occurrence matrix. And in this case 1 important thing is the P_d (i,j) is not symmetric matrix, it is the number of pairs of pixels having gray levels ij does not necessarily equal to the number of pixel pairs having gray level j. So, that is why the array P_d (i,j) is not symmetric.

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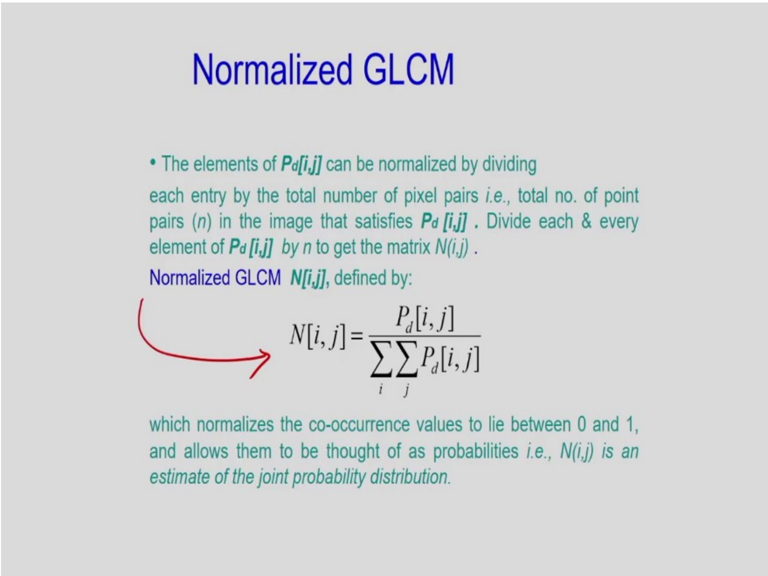

And after this as I mentioned earlier, so, we have to do the normalization. So, the elements of Pdij should be normalize. How to do the normalization, by dividing each entry by the total number of pixel pairs, that is total number of point pairs n in the image that satisfies P_d (i,j) and divide each and every element of P_d (i,j) by n to get the matrix N(i,j), that is the normalized GLCM, that is called a normalized GLCM, that I can calculate. Which normalizes the co-occurrence values to lie between 0 and 1.

And in this case the N(i,j) is nothing but, it is an estimate of the joint probability distribution. So, N(i,j) is an estimate of the joint probability distribution. So, you can see the procedure how to determine the normalized GLCM.

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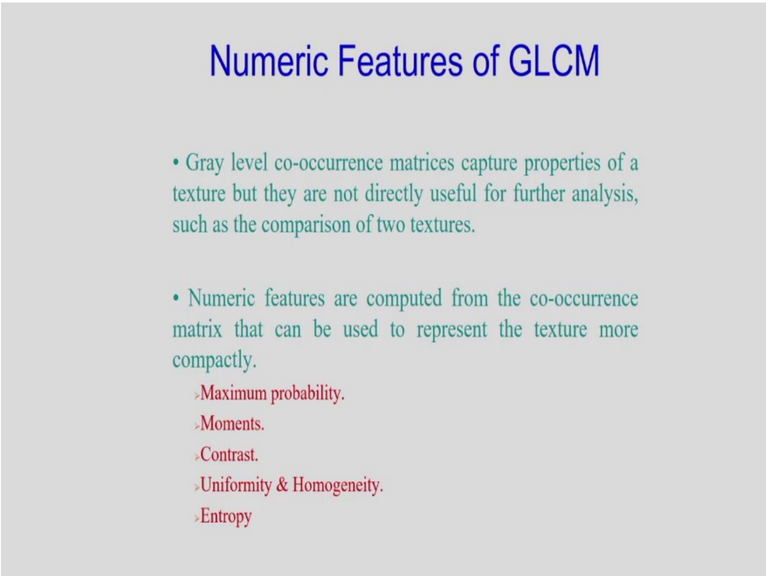

And from the normalized GLCM we can extract some features to represent a particular texture. So, what are the features I can compute or I can determine. The first one is the maximum probability I can determine, different moments I can determine, the contrast also I can determine, uniformity and homogeneity I can determine and one important parameter is the entropy, the entropy also I can determine from GLCM. So, first procedure is I have to determine the GLCM and After determining the normalized GLCM I can determine all these parameters.

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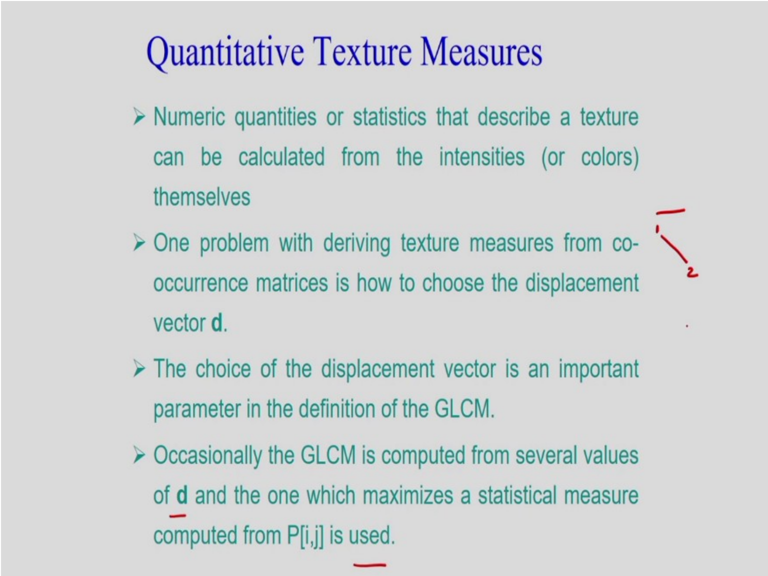

Now, in this case, one problem with deriving texture measures from co-occurrence matrix is how to select the displacement vector d. So, for this, the choice of displacement vector is an important parameter in the definition of the GLCM. So, that is why what I have to consider, that occasionally the GLCM is computed from several values of d. So, the GLCM is computed from several values of d and the one who is maximized a statistical measure computed from P ij is used. So, that is the procedure.

So, instead of considering only one displacement vector I can consider a number of displacement vectors, like this if I consider displacement vector, one displacement vector maybe like this, one displacement vector maybe like this, that is one pixel. Suppose, we consider 1 and 2 that means, the pixel 2 is located, one pixel along the right direction and one pixel in the bottom direction with respect to the pixel 1. So, for different displacements, I can consider the GLCM.

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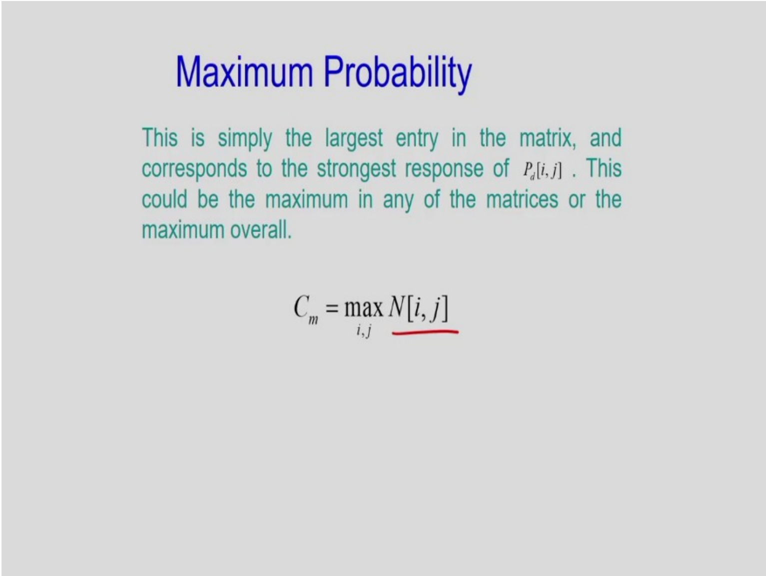

So, first parameter is the maximum probability I can determine. So, from that GLCM, N(i,j) is the normalized GLCM and I can determine the max corresponding to these variables i and j. This is simply the largest entry in the matrix and corresponds to the strongest response of the P_d (i,j) . This could be maximum in any of the matrices or the maximum overall. So, first parameter I can determine that is the maximum probability. This is simply the largest entry in the matrix and corresponds to the strongest response of the P_d (i,j) that I can determine. So, still the maximum probability I can determine from normalize GLCM.

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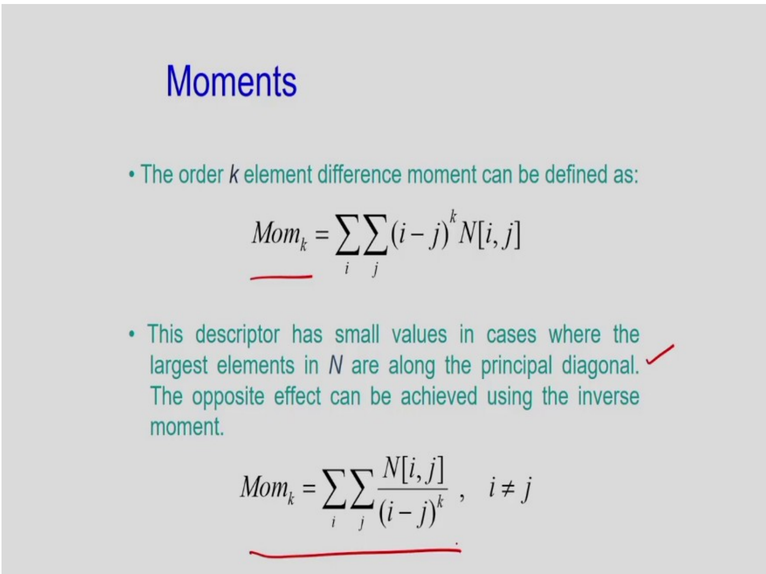

I can determine the moments. So, you can see the moments I am determining, the order K element difference moment I can determine. This is nothing but $(i-j)^k$ and I am considering

$N(i,j)$, $N(i,j)$ is the normalized GLCM. This descriptor has small values in cases where the largest element in n are along the principal diagonal, that you can verify. So, that is the order k element difference moment we can determine and this descriptor has small values in cases where the largest element in n are along the principal diagonal and the opposite effect can be achieved using the inverse moment. So, I can also determine the inverse moment by using this expression and I can get the opposite effect.

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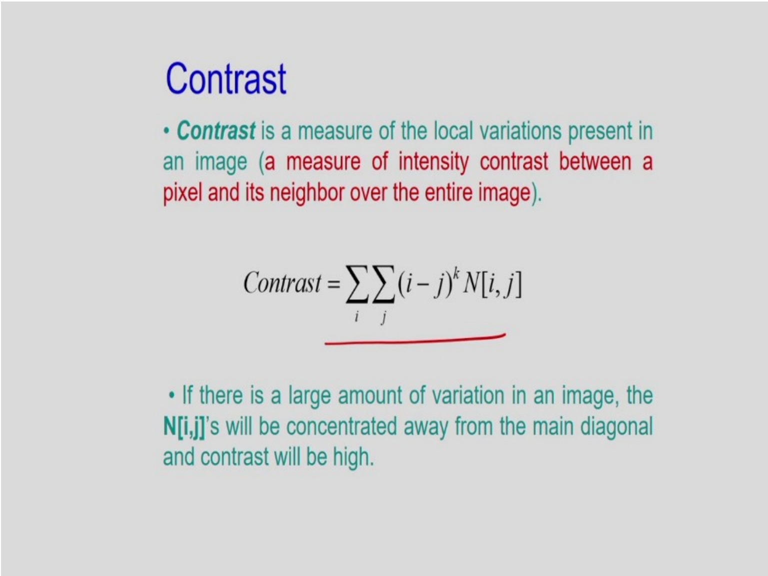

Next one is that I can determine the contrast information. Contrast is a measure of the local variations present in an image. So, by using this expression, and that is from the GLCM, you can determine the contrast. A measure of intensity contrasts between a pixel and its neighbor over the entire image, that I can determine. If there is a large amount of variation in an image the $N(i,j)$ will be concentrated away from the main diagonal and the contrast will be high in that case.

So, that also you can verify you take one simple text our image, and you can determine the contrast from the GLCM. And in this case, if I consider the large amount of variation in an image, then corresponding to these $N(i,j)$ will be concentrated away from the main diagonal. And in that case, the contrast will be very high, that you can verify, that you can see.

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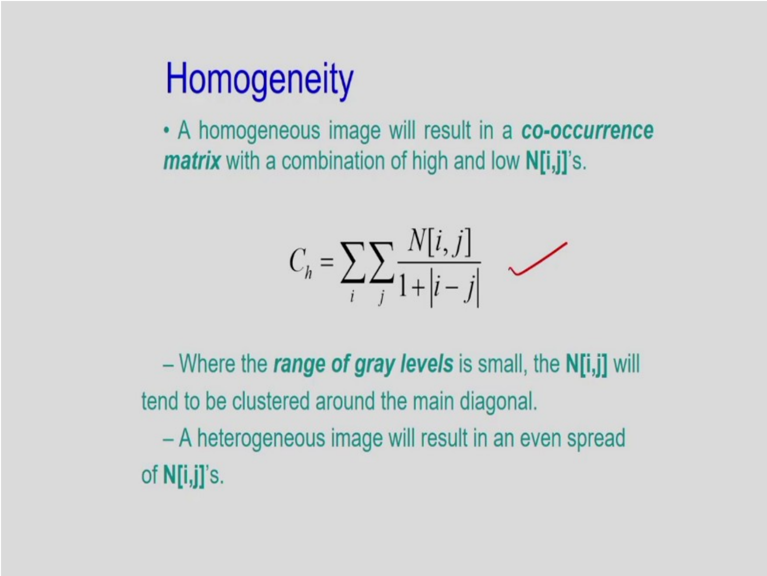

Another parameter is homogeneity. A homogeneous image will result in a co-occurrence matrix with a combination of high and low $N(i,j)$. So, you can determine the homogeneity by this expression. And in this case, the range of gray levels is small, suppose the range of the gray level is small, the $N(i,j)$will be clustered around a main diagonal.

So, that means, when the range of the gray levels is small, the $N(i,j)$will tend to be clustered around the main diagonal, that you can verify also. And a heterogeneous image will result in an even spread of $N(i,j)$s, that you can also verify. One is the homogeneous another one is the heterogeneous image you can represented by this parameter, that is the parameter is homogeneity parameter.

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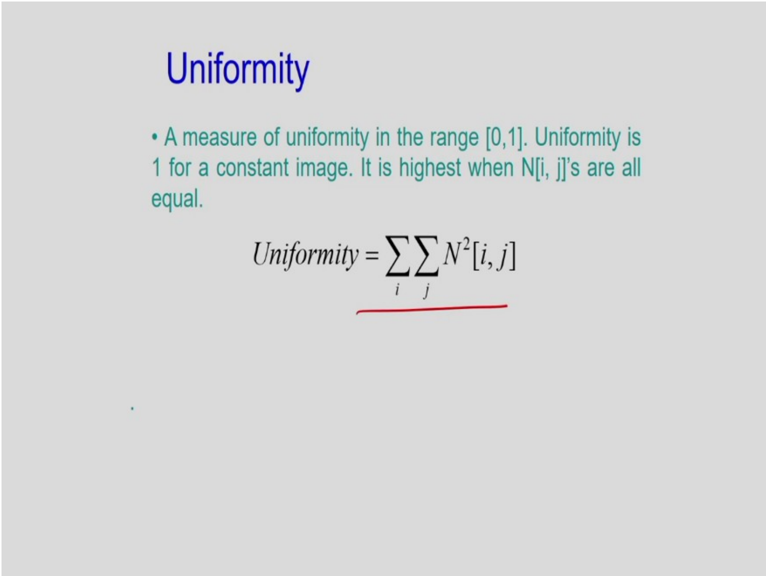

Another parameter is the inner property a measure of any property in the range of 0 and 1 and uniformity is 1 for the constant image, it is highest when $N(i,j)$'s are all equal. So, from this expression, it is evident that it can measure the uniformity of an image. So, for a constant image the uniformity will be 1, it is highest when $N(i,j)$s are all equal. So, for constant image I will be getting 1, the uniformity will be 1.

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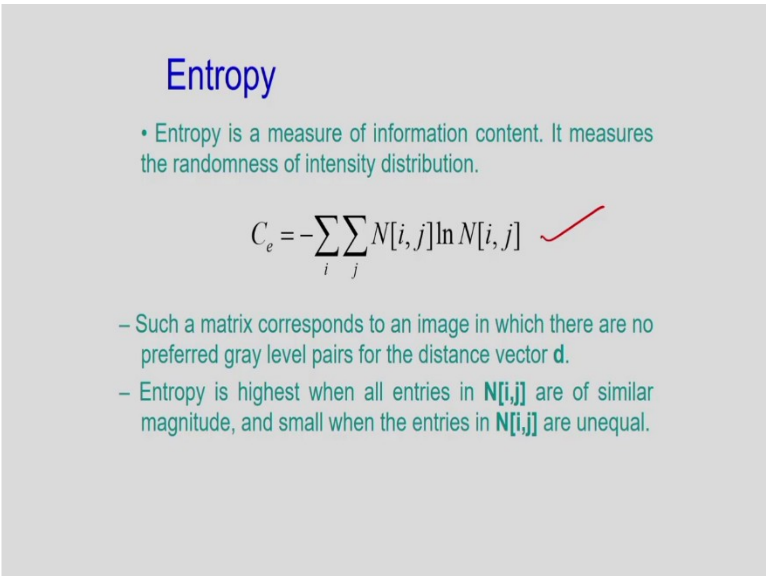

And finally, another important parameter, that is the entropy. Entropy is a measure of information content and it measures the randomness of intensity distribution. So, by using this expression, you can determine the entropy, the entropy from GLCM you can determine and such a matrix corresponds to an image in which there are no preferred gray level pairs for the distance vector d. Entropy is highest when all entries in $N(i,j)$are of similar magnitude and the entropy will be small when the entries in $N(i, j)$ are unequal, that you can verify from this explanation.

So, entropy is highest when all entries in $N(i, j)$ are of similar magnitude and small when the entries in $N(i, j)$ are unequal, because entropy measures the randomness of intensity distribution.

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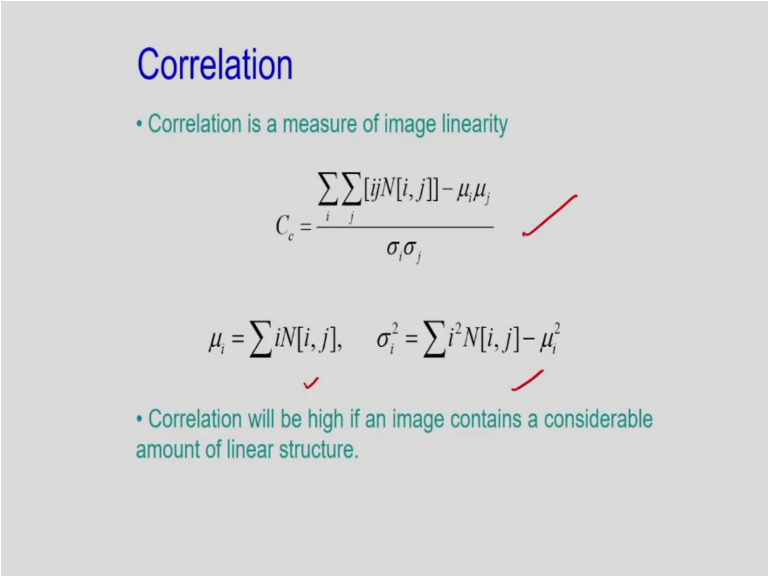

So, another parameter you can determine from GLCM that is correlation. Correlation is a measure of image linearity. So, you can see by using this expression, you can determine the mean and variance you can determine and from this you can determine the correlation also you can determine, that is that measure of image linearity. Correlation will be high if an image contains a considerable amount of linear structure. So, from this you can see the image linearity. So, all these parameters you can determine from GLCM.

So, this is the statistical method. In a statistical method, the inner parts case you can determine the moments image moments you can determine from the histogram of the image like the first order moment you can determine, the variance you can determine, the third order moment you can determine, the fourth order moment also you can determine, roughness factor also you can determine.

But the problem already I have mentioned that the spatial information is not available. So, that is why we have considered the gray level co-occurrence matrix. And how to determine that GLCM we have explained for different displacement you have to do and after this we can extract these parameters, these quantities like the maximum probability element difference moment of order k and also you can determine the uniformity entropy, all these parameters we can determine from the GLCM.

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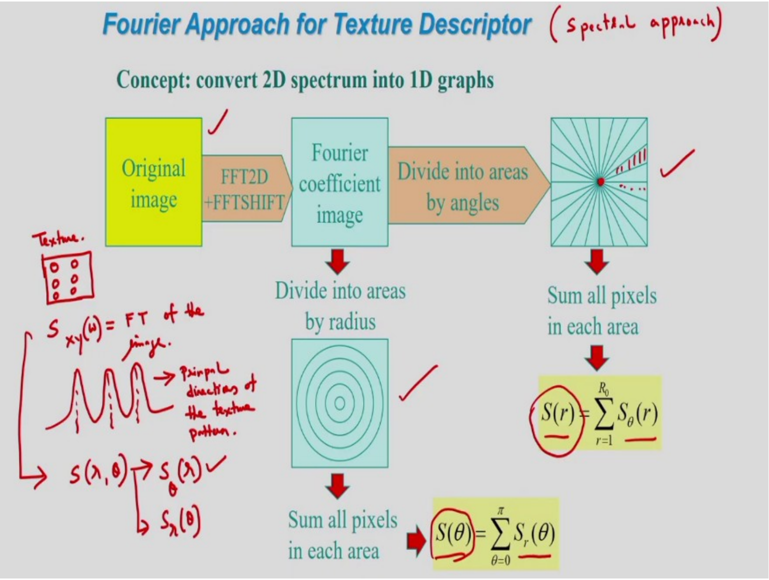

The next technique is the Fourier approach for texture representations. So, in this block diagram, I have shown the Fourier method. You can see the original image I have shown and after this I have to determine the 2d Fourier transform of the image. But before applying the 2d Fourier transformation, what I have to do, I have to do the preprocessing that means images multiplied by minus 1 to the power x plus y. And after this, I have to determine the 2d Fourier transformation. So, what is the main concept of the spectral approach, this is called a spectral approach, spectral approach.

This Fourier transform approach is called the spectral approach. So, suppose a Texel, this Texel is repeated like, this I have the texture that means, you can see some regularity in the texture that is nothing but the periodicity. So, this is my texture and, in this case, you can see regularity in the texture that is nothing but the periodicity. So, that means, the Fourier spectra of the image should exhibit strong components representing the periodicity of the texture elements.

So, for this what I have to consider, I have to determine the Fourier transform of the image. So, suppose this is the Fourier transform of the image, Fourier transform of the image I have to determine. Suppose I have the prominent peaks in the Fourier spectrum, the peaks are like this. The prominent peaks in the polar spectrum give the principal direction of the texture pattern. So, that means, if I consider these peaks, then in this case it gives the principle and directions of the texture pattern.

And also, the location of the peaks, if you see the location of the peaks, the location of the peaks in the frequency plane gives the fundamental spatial period of the patterns and we can eliminate the periodic components by filtering. Then in this case, I have the only the non-periodic elements, which can be described by statistical methods. So, you can see, first I have to determine the Fourier transform of the image.

And the prominent peaks in the Fourier spectra give the principal direction of the texture pattern and also the location of the peaks in the frequency plane gives the fundamental spatial period of the patterns. Also, I can eliminate any periodic components bias filtering. Then, in this case, I will be getting the non-periodic image elements which can be described by statistical methods as $S_{x,y}(\omega)$ that is the Fourier transform of the image. In polar form, in polar form, I can represent like this $S_r(\theta)$ this is in the polar form.

In the polar form what are the things I can do, $S_r(\theta)$ also I can consider and another one is I can consider $S_r(\theta)$. So, what is s theta r, theta is fixed and, in this case, r is variable, theta is fixed. So, it shows the behavior of the spectrum along the radial direction from the origin. The first one is that theta is fixed, but r is not fixed. In the second case $S_r(\theta)$, r is fixed, but theta is not fixed. That shows the behavior along the circle centered on the origin that is the behavior of the spectrum.

So, I will show in the figure here you can see. So, first what I am doing, I am continuing the original image after this I am doing the pre-processing, that is the image is multiplied by minus 1 to the power x plus y, after this I am determining the Fourier transformation. In the two cases you can see, I am considering that this case, the first case what I am considering I am determining s r, so for this I am considering $S_r(\theta)$, that means that theta is fixed and r is variable.

So, that means sum all pixels in each area. So, thus I am summing the pixels in each area, suppose this area I am considering, so summing all the pixels in each of the areas. So, what is the meaning of this? It shows the behavior of the spectrum along the radial directions from the origin. So, origin is this, this is my origin and it shows the behavior of the spectrum along the radial direction from the origin. So, I can determine the parameter, the parameter is S_r.

So, this parameter I can determine. So theta is fixed, and I am considering r is from 1 to r0, the maximum value. In the second case, what I am considering divided into areas by radius that I am considering. So in the second case, what I am considering, r is fixed, I am considering S_r, theta, that means I am considering the fixed r. And in this case, I want to determine or I want to see the behavior along a circle centered on the origin. That is sum of all the pixels in his area I have to determine and I am getting S theta.

So these two parameters I am getting one is S_r, another one is S theta. In one case, that the theta is fixed, in another case, the r is fixed. So, the meaning is first I have to determine the Fourier transform of the image. And after this I have to convert into polar coordinate, the polar coordinate is r and theta. And I have to consider these two cases, in one case the theta is fixed, in another case the r is fixed.

In one case, I want to observe the behavior of the spectrum along the radial direction from the origin. In another case, I want to observe the behavior along the circle centered on the origin. So, this is the objective of the Fourier transform approach for texture representation.

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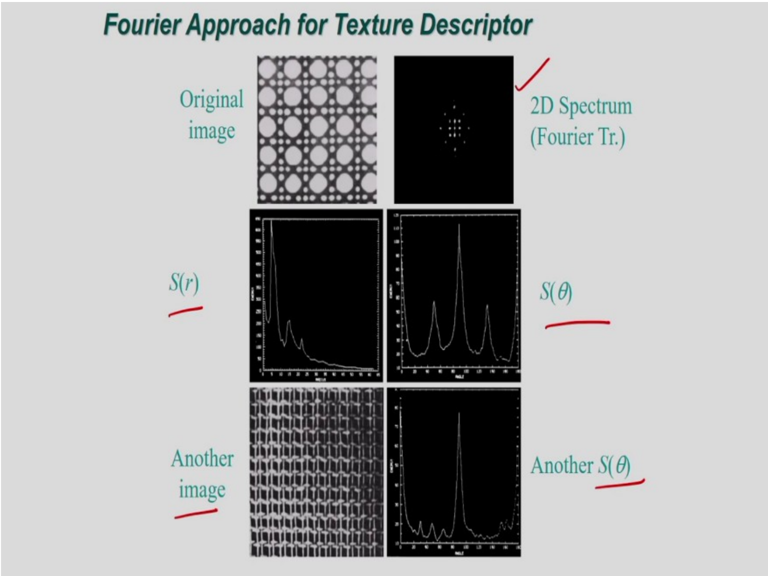

And in this example, you can see I have considered the original image and after this you can see the 2d Fourier transform of the image and you can see these two parameters one is S_r, another one is S theta. And corresponding to another image I am considering another image corresponding to another image you can see the value of S theta you can see the spectrum S theta. So, by using this S r and the S theta we can describe a particular texture.

So, up till now, I discussed about the concept of texture, I have defined the texture what is texture. After this there are 4 research directions one is texture classification, one is texture segmentation, one is texture synthesis, and one is shape from texture. After this I discussed about the statistical method for texture representation. So, for this I considered one very good method, that is the GLCM the gray level co-occurrence matrix and from the GLCM I can extract different parameters.

After this I discussed about the spectral approach, that is the Fourier transform approach for representing a particular texture. So, in my next class, I will discuss another technique like Gabor filter, the local binary patterns. So, all these techniques I will be discussing in my next class. So, let me stop here today, thank you.