Digital Image Processing

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Lecture - 39

Object Representation and Description -III

Hello, welcometo the video lectureseries on digital image processing. Forlast 2 lectures, we have started discussion on the last phase ofimage understanding process that is representation and description of the regions present in an image.

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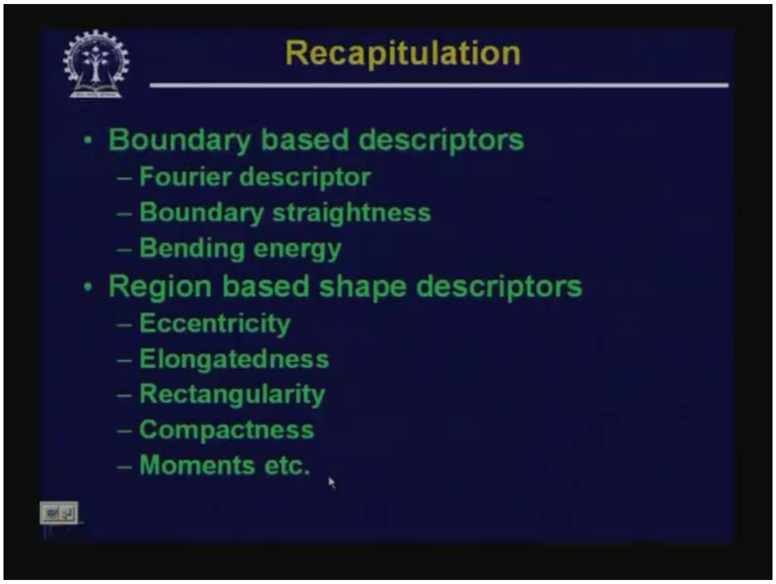

Tillour last class, for last 2 lectures,what we have d1 is we have found out some descriptorswhich we have saidare shape descriptors and we have said that this shape descriptors can be obtainedeither from the boundary from the region or from the region itself. So, in our last class,we have seen some of the boundary best descriptors like Fourier descriptor, then boundary straightnessandbending energy. Similarly,some other shapedescriptorswhich we have obtainedfrom theregion itself; some of them are eccentricity,elongatedness,rectangularity, compactness, moments etcetera.

Intoday’s lecture, what we are going todiscuss about is some other descriptors from the region itself.These are the descriptorsthat we will discuss;they take careof the surface nature, nature of thesurface. Youfind that all other descriptorsthat we have discussed earlier, those are the shape descriptorswhich are obtained either from the boundary of the region or from the inter regionbut they donot give you any ideaabout whatis the surface nature.Itsimply tells that what is shape of the object present in the scene.Intoday’s lectures, we are going to get some descriptors,derive some descriptorswhich will tell us about what is the shapeor what is thenature ofthe object surface.

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Sotypically,what we willbe talking about the region descriptorsand we will discussabout the region descriptors which arethe texture descriptors.Now, as wehave said earlier that such region descriptorswhich givesyou idea about the nature of thesurface,they may be derived fromthe colour of the surface or also may be derivedfrom the textureof the surface.The colour informationthat can be obtained,that we have discussed earlier when we discussed aboutthe colour image processing.

Today, what we will discuss is mostly the textures descriptor that is it will capture the texture informationof the surface.Now, when we go about this texture descriptor,the texture descriptors can be obtainedin variousways.So, 1of the technique that we will discuss is histogram moment based texture descriptor.Wewill also talk abouttheco-occurrence matrix basedtexture descriptorand we will also discussabout thespectral method or the spectral descriptorswhich are useful for describing textures.

Now, what isa texture?The texture normally refers to propertiesof the nature ofthe object surfaceor the structure of the object surface.So, what I mean bytexture,itisbetterexplainedwith some examples.So, let us see some example textures.

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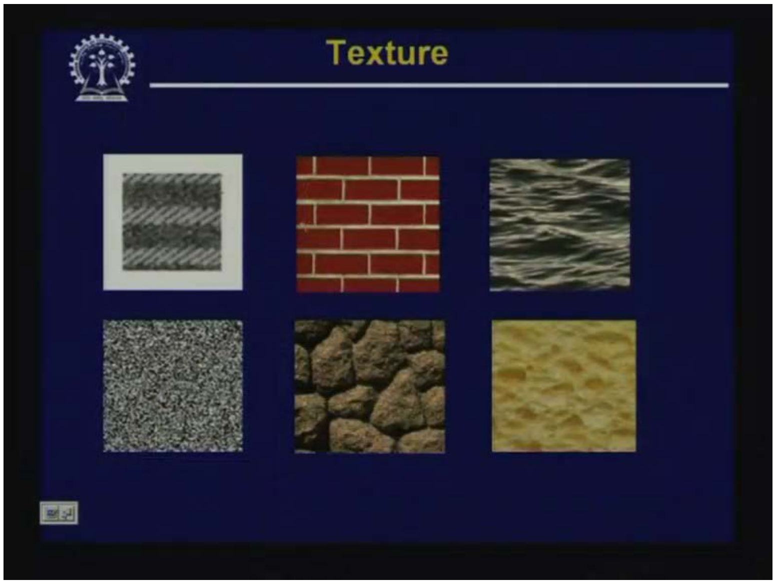

So, here you find that we have given four different6 different images and each ofthese imageshas some textures. So, as you findthat the texturecan be of various form;for example,the pattern ona cloth, the way in whichthe threads are weaved that also forms a texture, ifyou take the image of plane surface of say wood that also forms atexture, thetree lines,they also the forma texture.

So, there are various varieties oftexturewhich are available in nature and various varieties of texture which can alsobe generatedsynthetically. So, the notion of the texture, the concept of texture; this quite obvious intuitivelybutbecause of this wide variation oftextures, no précised definition of texture exists. So, what we can say isthe texture is something which consists ofmutuallyrelatedelements.

So, when we say that it is something that consists of mutually related elements;so basically, what we are talking about is a group of elements or a group of pixels. So, in some cases,say for example, in this particular case, you find that we can say that these textures contain some primitive elements and by repetitiveappearance ofthe primitive elements eitherit is completely periodic or semi periodic; so, by repetitive appearance ofthese primitive elements,what I get isa texture image.

These primitiveelements are the group of pixels which form a texture is calledthe texture element ortexts.So, as we saidthat noprécised definitionoftexture existsbutthe texture provides some very very importantinformation about the roughness or thesmoothness of a surface.Atthe same time, it also gives us the some information of theregularityof the surface. So, what are the waysin which we can obtainthe descriptorswhich describes a particular texture? So, thetexture descriptorscan be obtained in various ways.

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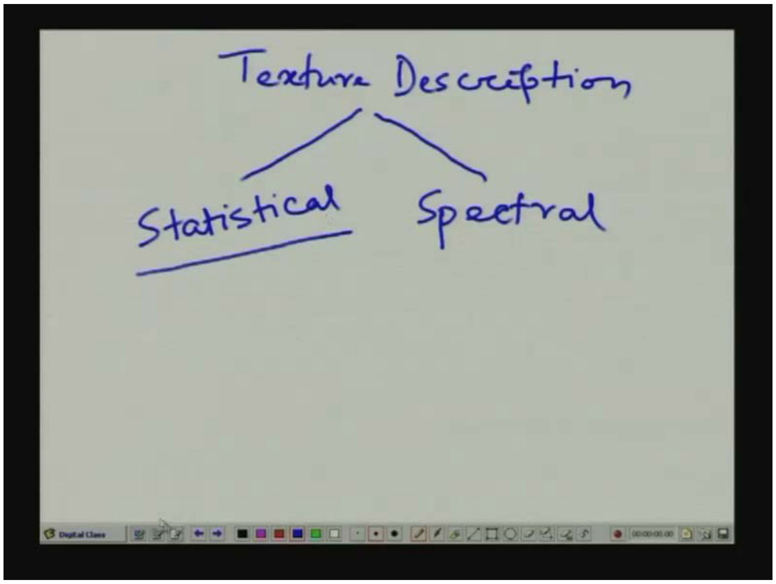

Wecan have texture descriptions which are broadly categorized into 2 categories.So, we can have texture description. So,1 of the ways in whichthe texture description can be obtained is statistical.So, we can have statistical meansto obtainthe descriptors of the texturesand the other ways of obtainingthe texture descriptors isfrom the spectral domain.Thatis ifyou take the Fourier spectrum ofthe texture image and from the Fourierspectrum, we can obtain sometextures,somedescriptorswhich describe the nature ofthe texture. Letus first considerwhat are the statistical descriptors that we can obtain from a texture image.

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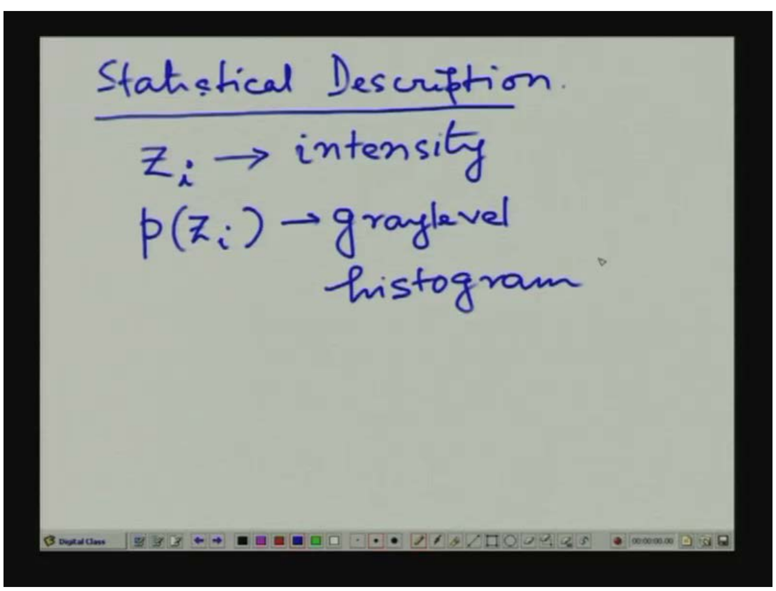

So, the simplest forms of statistical descriptors are obtained from the gray level histogram of a textureimage and what we do is you findout the momentsofthe gray level histogram. So, let us assumethat in a texture image;z is a variable,Z_i is a variable which represents the intensity of different pixels present in the texture image and supposep (Z_i),this representsthe intensity histogram or gray level histogram.So, from thisgray level histogram,we can find out different textures which are nothing but moments of different orders and the descriptorswhich are derived from these moments of the histogram.

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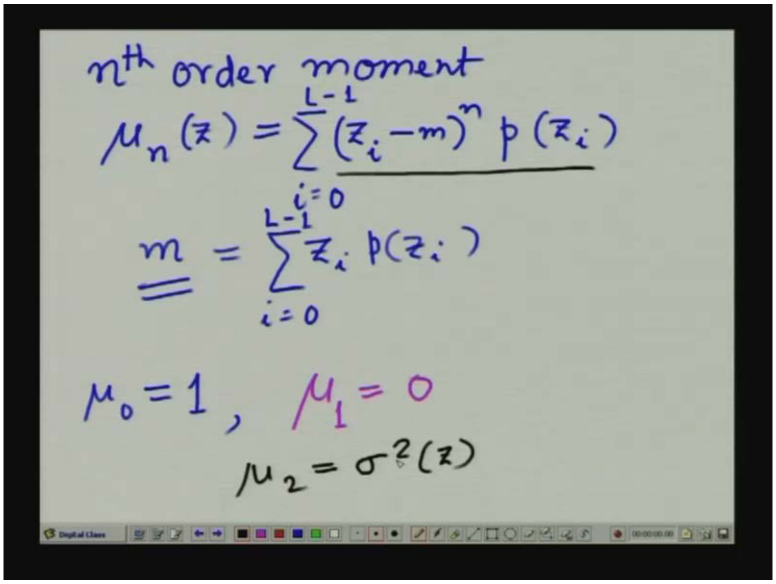

So, given a histogram p (Z_i), we can have an n’th order moment.So, n’th order moment of a histogram is defined like this;mu $_n$(z),this is n’th order moment is given by$Z_i$minus m to the power n into p (Z_i) and you take the summation for i is equal to 0 to L minus 1. Sohere, what we are assumingis that the intensity levels,the texture image has got L number of capital L numberof intensity levels varying from z 02z capital L minus 1.

So, there are capital L number ofdescript intensity levels and if p (Z_i) is the histogram of such a texture image, then we can obtain an n’th order momentof this texture image from the histogram as given by this definition. Now, in this particular case, m is nothing but themean.So, you define m as Z_ip (Z_i) where you have to summit up from i equal to 0 to capital L minus 1. So, this is what is the mean intensity value within the texture image.

Now, we can infera number of interesting properties from this n’th order histogram moment. Youfind that ifI take the 0’thorder moment that is mu$_0$ where value of n equalto 0; in that case, $Z_i$minus m to the power nthat becomes equal to 1. So, what we are left withis summation of p (Z_i) where ivaryfrom 0 to capital L minus 1. So, if I addall these different probabilityterms, thenet summation becomes equal to1. So,you find that in this particular case,the 0’th order moment of the 0’th order moment of this histogram is simply equal to 1.

Similarly, if I take the first order moment that is mu$_1$, you will find that mu$_1$ will be equal to 0 but very important is the second order moment mu$_2$. Sohere,you find following this same expression, mu_2 is nothing but Z_i minus m square p (Z_i), take the summation for i equal to 0 to capital L minus 1.

So, from this particular expression, you will find that mu_2 is nothing but the variance which we normallywrite as sigma square z. So, the second order moment is basically the variance of the intensity values present in the image and this variance is a very very important information because it tells us that what is the variability or what is the range of the intensity values which are present in a particular image in a given texture image and from this second order moment or the variance, we can derive very very important texture descriptor. So,we can definean important texture descriptor like this.

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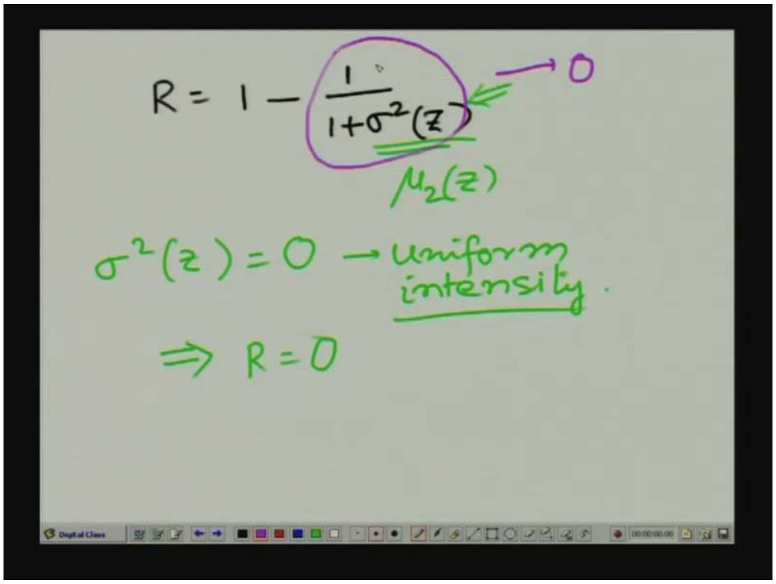

So, R is equal to 1 minus 1 upon 1 plus sigma square z andas we said that the sigma square z is nothing but mu_2 that is the second ordermoment. So, whatis the importance ofthis particular descriptor R? Youwill find that if I have a completely plane surface,a completely smooth surface of uniformintensity;in that case,the value of sigma square z orthe variance will beequal to 0 for uniform intensity region and in suchcase, because variance sigma squarez is equal to 0, you will findthat this complete expression R will become equal to 0 in such case.

So, if I have an image ofuniform intensity,the same intensity value for that, value ofR will be equal to 0. Butif I have variation on the image,the intensity variation in the image;in thatcase,sigma square z willbe non 0valuesand more the variation is the value ofthe sigma square z will even be more. So, as the value of sigma square is zincreases,in this particular case, you will find that 1 upon this particular quantity,1 upon 1 plus sigma square z,this tends to be 0. Asyou increase sigma square z more and more, the value of this quantity 1 upon 1 plus sigma squarez,this tends to be 0.

So,as the surface becomes more rough in the sense thatis more variation of intensityvalues in the image, the value of R turnsto be 1. So, for a completely uniform surface, we have value of R equal to 0whereas forrough surface, depending upon the degree of roughnessor the degree of variation of intensityvalues, the value of R increases and it reaches a maximum valueequal to 1.

So, it is the value ofthis particular descriptor R which is very very important which catches what is the variation of the intensity values in a given texture. So, we havesaid, we have seen the meaning ofthree different histogram moments;mu$_0$ - the 0'th order histogram moment which is equal to 1,mu$_1$ - the first orderhistogram momentwhich is always equal to 0.

So, these 2 histogram momentsdoes not give you any information about the nature of the texturewhereas the secondhistogram momentmu$_2$ whichisequipollent tovarianceofthe intensity values in the image; from this mu$_2$, we cangenerate an important texture descriptor which for a flatsurface or for a uniform image will be equal to 1and it willgradually increase and reaches a value1for a uniform surface, this value becomesequal to 0and as the surface roughness increases,the value of Ralso increasesand it reaches a maximum value of1 depending upon the degree of roughness of the surface.

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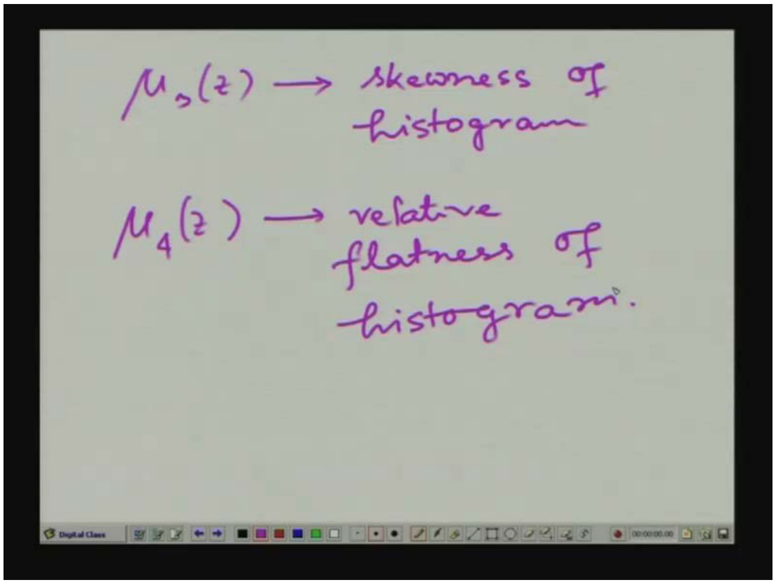

Now, there areother moments, say for example,mu$_4$ ormu$_3$ that is the third order moment;you will find that this mu$_3$ (Z)third order moment, thistells you thatwhat is the skewnessof the histogram.Similarly, the fourth order moment mu$_4$, this tells us the relativeflatness of the histogram.

Sonormally,as texture descriptor, the texture descriptors which are generated which are derived from the gray level histogram, the descriptors which are used upto fourth order histogram moments, the moments of higher order like fifth order oreven higher orderabnormally not used but if you use them, they will give more and more final descriptors of the texture.

So, though this histogram moment based descriptors, they are very simple but they have one problem.Theproblem isthesehistogram descriptors, histogram moment based descriptors,they donot provide us any information about the relative position of the pixels.Butas we have seen, you will find that in this particular texture, the intensity values,theintensity values at a position with respect to some other positionthat carries lot ofinformation.

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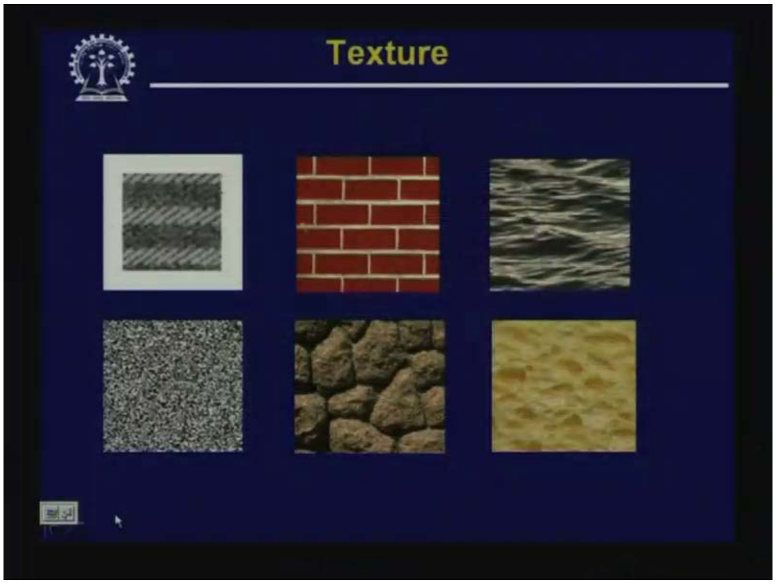

So, what is the way in which this relative position information can also be obtained for the texture images, that information that relative position informationalso gives you a lot of important descriptors which are useful for describing a texture.

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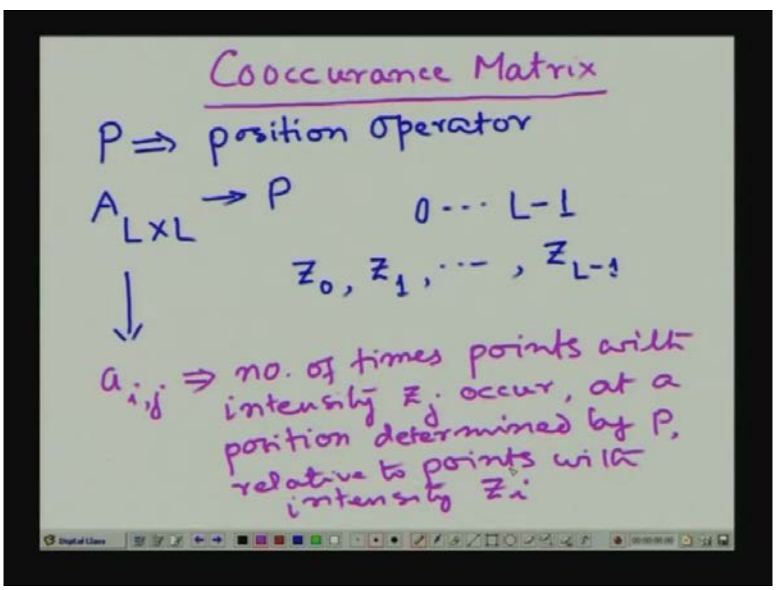

So,towardsthat we will talk about anothertechnique for obtainingthe texture descriptorswhich are obtainedfrom what is called co-occurrence matrix.So, as we said that what we are interested in is along withthe intensity values, the relative positionsof the points with various intensity valueswithin the texture; so, we have to define anoperator.

So, we define an operatorsay P which we call as position operator and before deriving the co-occurrence matrix, we will generate a matrix say Awhich will be of dimension capital L by capital Land this matrix A will be generated using the constraintwhich is specified by the position operator.So, we are saying that we will generate a matrix of A of dimension capital L by capital L.So, here again our assumptionsis that the intensity values which are present in the texture image varies from intensity gray levelsvaries from 0 to L minus 1.So,we will have gray level ofz_0 value,we will have gray level of z_1 value and like this the maximum gray level that we can have is $Z_{L \text{ minus } 1}$and in this matrix, capital A which is of size capital L by capital L, a particular element say $a_{i,\ j}$this will indicate the number of times points with intensity value$Z_j$occur at a position determined by P relative to points with intensity Z_i.

So, what we are doing is we take a point with certain intensity value within the texture image,then following our position operator capital P, we come to some other point.So,I find that what is the intensity value; suppose the intensity value at the location that we are considering is $Z_i$and following the position operator P, the other location where I come the intensity value of that location is say Z_j; so this $a_{i,j}$ thisindicates that how many times such apair $Z_iZ_j$as indicated by the location operator capital P appears within the given texture.

Obviously, in this particular case,i and jthe indices i and jwill have values within the range0 to capital L minus 1 so thatI have a matrix A of sizecapital A by capital P.So, what I mean by this,this will be better explained with help of an example.

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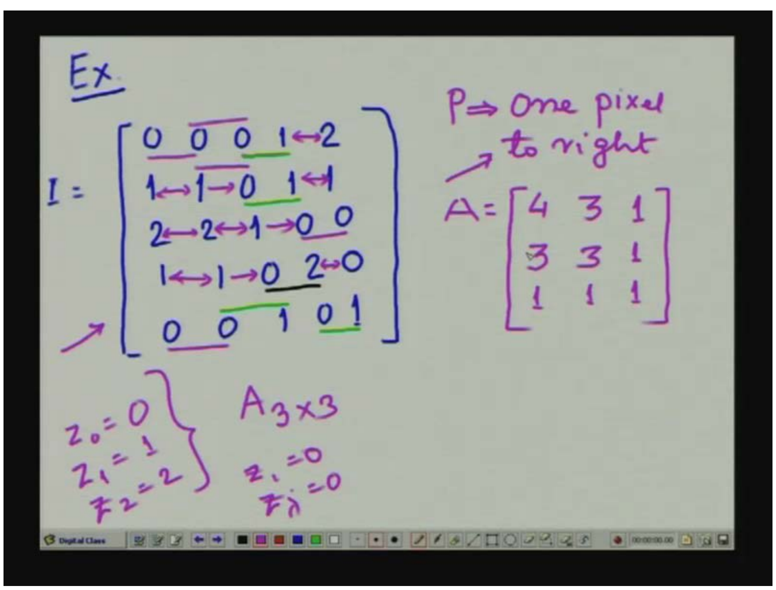

So, let us take anexample matrix assuming thatthat is the representative of a particular texture imagethat we are considering.So, let us take an examplelike this;so we have agiven matrix, image matrixsay iwhich is given by0 0 0 1 2,1 1 0 1 1, 2 2 1 0 0, then say 1 1 0 2 0, then I can have say 0 0 1 0 1.

Sosuppose, this our given image and let us assume that the position operator that we are saying say P, this position operator indicates 1 pixel to right.So, from this given image and this position operator; how we cangenerateour given matrix A?So, here you notice that this particular imageor the sample of the image that we have said, this contains three distinct intensity levels.

So, those intensity levels aresay Z_0 isequal to 0.So,0 is one intensity level within this image.Z_1 is equal to 1 andZ_2 is equalto 2.So, there are 3distinct intensity levelswithin this image.So,the matrix A that we calculate willbe of dimension 3by 3.Now, we have find that following this positionoperator, whatI have to do is following this position operator,I have to get the pair of pixels and we have to compare and we have to count that for thosepair of pixels, whatever is the pair of intensity values, how many times that pair appear within our given image.

Sofirstly,let us assume that$Z_i$is equal to 0,$Z_j$is also equal to 0.So, here you find that since it says that P -theposition operatoris1 pixel to theright;so I come to a pixel $Z_i$which is having a valueZ_i equal to 0andI have to goto the next pixel to the right where the value will also be equal to 0.So, how many times,I have to count how many times this 00 pair;one in the horizontal direction at a distance of 1 pixel appears within the given image.So, here we find that I have one suchpair;this is anotherpair, this is another pair and this is onemore pair.So, numberof timesthis 00pairappear with in our given imageis 4.So, when I computethis matrix A,the 00locationA_{00} will be equal to 4.

Similarly, how many timesA_{01} will appear within this image?So, A_{01}, this is one occurrence;let me usesome other colour,sothis is oneoccurrence of A_{01}, this is another occurrence of 01,thisis another operands of 01.So, this is 01 pair appear thrice within this given image.So, A_{01} locationwill containa value equal tosorry this is one more location pair A_{01} occurs.So, this A_{01}element will have a value is equal to 3.So, this will have the value equal to 3.

Similarly, let us say how many times A_{02} appear in this image.So A_{02}, we can find thatthis is the only occurrence of A_{02} in this particular image.So, this location A_{02} will have a value equal to 1.Similarly,I have to check how many times 10 appear in this particular image.So, you will find that the number of times 10 appear in thisimage ishere I havea 10transition, this one, here also I have 10transitions,here also I have 10transitions,10 pair.So, A_{10} will have a value equal to 3.

Similarly A_{11}, this is one pair, A_{11} this is one more pair, A_{11} this is another pair. So, A_{11} will also have a value equal to 3. A_{12} this is 1 pair, A_{12} and possibly this is the only pair A_{12}within this image.So,A_{12} will also have a value equal to 1. Similarly A_{20}, you come tothis particular image, you will find that this is one pair A_{20} and there is no other occurrenceof A_{20} pair within this given image.So,A_{20} willalso beequal to 1.

Similarly A_{22}, this is the only pair within this image.So,A_2sorrythis is A_{20}then A_{21}, A_{21},this is the only occurrence of A_{21} within this image.So,this A_{21}will also be equal to 1. SimilarlyA_{22},this is the only occurrence ofA_{22}. So, this element will also be equal to1.So, as a result,I get myA matrixwhich I justcomputed in this particular form.

Now, from this matrix A,we can computethe co-occurrence matrixfor this particular image. Howdo we get the co-occurrence matrix?If I takethe total number of occurrences of all thesepairs within this imagewhich follows which satisfies our positional operation, the positional restriction as given by the positional operator capital B; thenyou find that the total number of or the total such occurrences within this matrix is say n is equal to in this particular case if you take the summation of all these elements, it will be equal to 19. So, if I divideall the elements of matrix capital A by this total number ofoccurrences,then what I get is what is calledco-occurrencematrix.

So, in thisparticular case,our co-occurrence matrix C will be simply given by 1upon 19times capital A. So, what are to do is I have to divide each and every element in the matrix capital A by the total number ofoccurrences of pairs of intensity values as dictated byour positional operator capital P and this resultant matrix that I get is our co-occurrencematrixes. So, what does thisco-occurrence matrix tell us?

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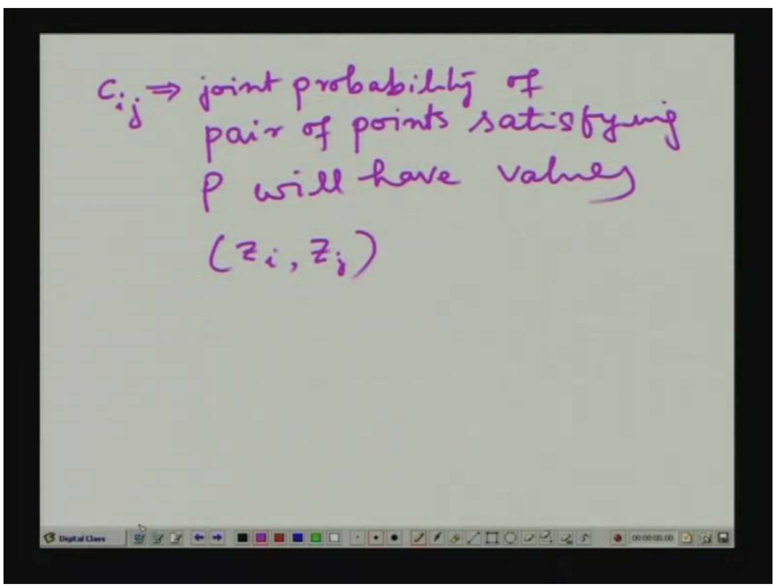

Everyelement say C $_{ij}$within this co-occurrence matrix,itindicates the joint probability ofpair of points that satisfies; so pair of pointssatisfying P will have values $Z_i$and Z_j. So, when I have this co-occurrencematrix, every element C $_{ij}$within this matrix thatindicates the joint probability ofpair of pointswhich satisfies our positional operator capital P that will have values $Z_i$and Z_j.

So, you findthat in histogram based moments oravailable histogram based descriptors that we havegenerated, we did not have any positional information.Butwhen we have a co-occurrencematrix, in the co-occurrence matrix, we have the positional information as well as the intensity relation of the points following certain positional information.

So, the question is once we have defined such C_{ij}or once we have obtained a co-occurrencematrix; what is the algorithm following which we can obtain a co-occurrence matrix? Sonow, let us see that what kind of algorithm can be usedto obtain thisco-occurrence matrix.

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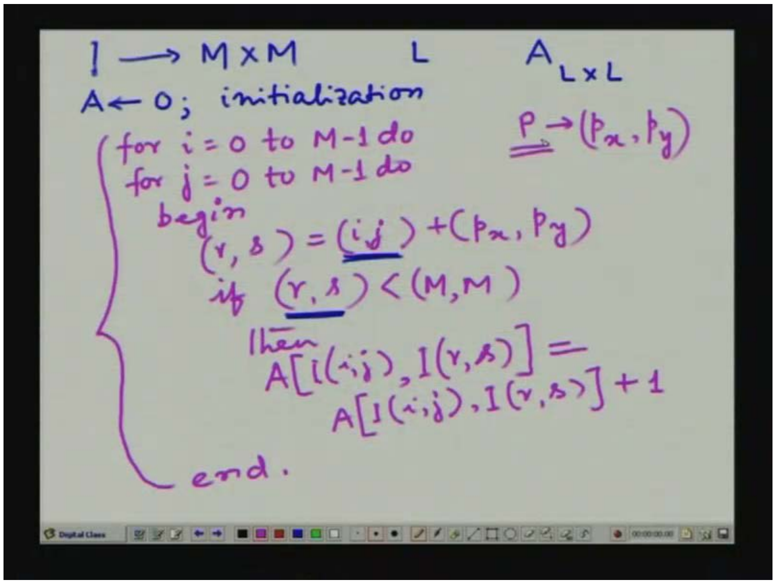

So for this, let us assume that we have our image I given image I which is of size say capital M by capital M. So, this capital M by capital M is our original image and let us assume that the intensity levels, the discrete intensity levels, the number of discrete intensity levels which are present in the imageis say L. So, first of all, what we have a do is we have to generate a matrix capital A whose size will be capital L by capital L. So, an algorithm can be written like this; this matrix capital A of size L by L can be initialized to 0.So, this is my initialization.What I mean by this is we make every element in the matrix capital A equal to 0.

Thenour algorithm can walk in this fashion; say for i equal to 0 to capital M minus 1 do forj equal to 0 to capital M minus 1 do begin, so here comes the operation for computation ofour matrix capital A. So, for this computation what I assume is suppose the position operator P is indicated by a vector because as we said that the position operator says that given a particular pixel location, what is the location of the other pixel that we are interacted in.So, that can be obtained simply by some vector addition operation.

So, I assume that P is indicated by a victor, by a position victory whose comp1ntsare say $P_x$in the x direction on P_y in the Y direction. So, what I have is ij maybe index ofone particular pixel location and from this,I generate the index of another pixel location (r,s) which is nothing but the vector addition ij plus (P_x, P_y). So, this is a vector addition operation.

ThenwhatI have to do is I have to compute whether this image index, image point index(r, s) thatyou have generated by this vector addition operation, whetherthat is within our image or not. So,I have to check if(r,s), this vector is less thanM, M. Thenonly this (r,s) position is within our image because our image is of dimension capital M by capital M which are indexed from0 to capital M minus 1 and 0 to capital M minus 1. So, if this point is satisfied,this condition is satisfied; that means (r,s) point remains in our image.

So, if this is satisfied, then what I see is what is the intensity value at location ijandwhat is the intensityvalue at location (r, s)? So, using those intensity values as indices in our matrix capital A,I can increment thecorresponding location in matrix capital A by 1.So,our operation will be that if this is true, then A [I (i,j),I (r,s)], these has to be incremented by 1.So, this becomes A [I (i,j),I (r,s) plus 1 and this is where our iteration ends.

So,you find that at the end of execution of this, the matrix A will contain the number of times a pair of pixels having a pair of intensity values occur within the image I where the these pair of pixels follow the position relation as indicated by this position operator or position victor capital P. Soonce I get this A matrix, the matrix capital A; then from this matrix capital A,if I add all the elements in the matrix A and divideevery element of the matrix capital A by that summation,what i essentially i get is our co-occurrencematrix capital C.

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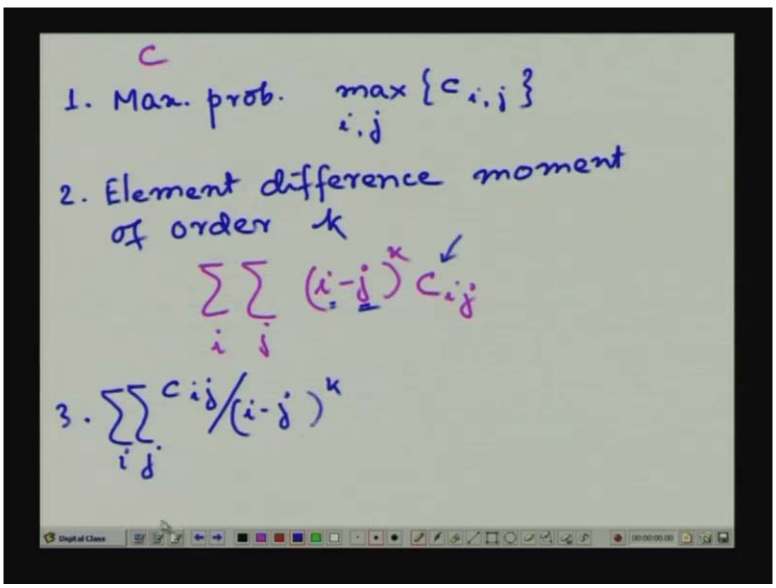

Thenext operation to obtain the featuredescriptors, the texturedescriptors from thisco-occurrence matrix is you analyze this co-occurrence matrix to generate various kinds ofdescriptors. So, what are the different typesof descriptors that we can obtain from the co-occurrencematrix?Thefirst type of descriptors that we can obtain from the co-occurrencematrix is the maximum probabilityor this is nothing but maximum of C_{ij}over all ij.

So, what is this maximum probability indicates?This maximum probability indicates the strongest response to the position vector P of the given image I. So, this will indicate that whether given a position operator say capital P if the capital P indicates a position in the horizontal direction, then how the texture is responding to that horizontal variation.

Theother kind of descriptor that we can obtain from this co variance matrix is what is called element difference moment oforderk and this element difference moment is defend like this; i minus j to the power k$C_{ij}$where we have to take the summation over i and j.So, this is what is called the element difference operator and this element difference operator, you will find that it will be low if higher values appear along the main diagonal because along themain diagonal,we will have i is equal to j, so if higher values of C_{ij}they appear along the main diagonal of the co-occurrencematrix; then this elementdifference moment, k'th order elementdifference moment will assume a low value.

Similarly, we can have the other operator which is just inverse of this that is C_{ij} dividedby i minus j to the power kand you have to take the summation of these over i and j and this gives you just the inverse effect.That means if the higher element values if larger will the value ofC_{ij} appear along the main diagonal; in that case,this particular value will have this particular quantity will have a higher value and if the elements along the main diagonal, they have low values, then this will also give a lower value.

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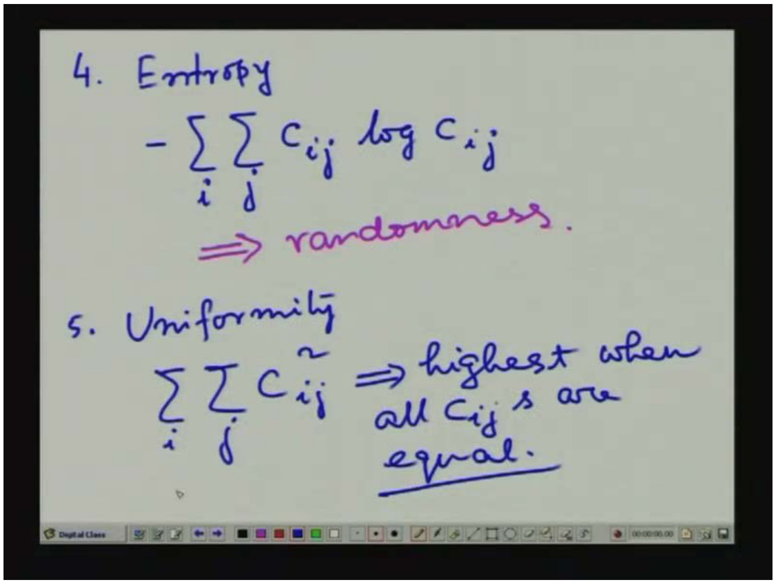

Theother descriptors that we can obtain, fourth descriptor from this co-occurrence matrix C is what is called entropy and we know that an entropy is defined in this manner; we have C_{ij}, then log of $C_{ij}$and we have to take the summation over i and j and as we know that this entropy is nothing but a measure of randomness,so it tells us that how random the given texture measures.

Similarly, the othertexturemeasure that we can obtain from the co-occurrence matrix say fifth measure is what is called uniformity andwhich isdefined as summation of C_{ij}square and here again, you have to take the summation over i and j.So, we will find that this particular value uniformity, it will have highest value when all C_{ij}'s are equal.That means our texture is the co-occurrencematrix for that particular texture is a uniformco-occurrence matrix.So, these are the various texture descriptors that can be obtained from theco-occurrencematrix.

And, as we have said, in our algorithm that given a texture image, how we can compute the co-occurrence matrix of the giventexture image.So, these are the differencedescriptors, the texture descriptors whether they are used, whetherthey are derived fromhistogram moments or they are derived from the co-occurrencematrix, these are the statistical descriptors that we can have of a given texture.

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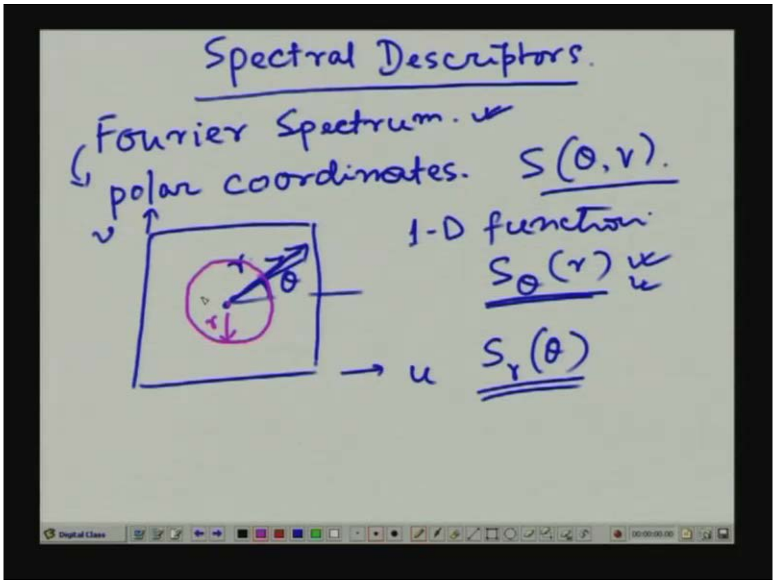

And, as we said that along with these statistical descriptors, we can also generate some spectral descriptor.That means we can generatedescriptors from the spectral domain.So, to obtain the spectral descriptors, what we have to do is we have to find out what is the Fourier spectrum of the given image.So firstly, we have to find out the Fourier spectrum.

So, what we get from this Fourier spectrum?Theprominent peaks in the Fourier spectrum will tell us what is the principal direction of the texture patterns.That is whether the principal direction of the texturepatternis horizontal or principal direction of the texture pattern is vertical or they are diagonal and so on.

So, this principal direction of the texturepatterns is obtained from the Fourier spectrum or the prominent peaks in theFourier spectrum and another information that we get is from the location of the peaks.So, the location of the peaks within theFourier spectrum tells you what are the fundamental special periods of the patterns.Aswe hadseen earlier that whenever you have a texture,the texture has some special variation and this special variation can have some periodicity, theperiodicity maybe strictly defined or it may not be strictly defined.

So, the location of the peaks,location of the prominent peaks in the Fourier spectrum, theygive you information about what are the fundamental periods of the texture pattern. Now, for convenience of computation,what we do is this Fourier spectrum is converted into polar coordinates.So, polar coordinate means I have the Fourier spectrum which is originallyCartesian coordinate.So,I have directions u and v and these I would like to convert in the polar coordinate.

So, in polar coordinate, a particular direction theta, if I find out the variation in aparticular direction of theta;so each value of theta will give me a 1 dimensional functionwhich I call as $S_{theta}(r)$ because r is theradial distance.So, if I convert this into polar coordinates,the Fourier spectrum into polar coordinates; then for each value of theta, so what I have is now the Fourier spectrum which is represented in the form of $S_{theta}(r)$ as we are going for polar coordinate representation and each value of theta gives us a function a1 dimensional function which I can represent as $S_{theta}(r)$.

Similarly, for each value of r that is the radial direction,I can have a 1 dimensional function which I can represent as S_r theta.So, what do this $S_{theta}(r)$ and $S_r$theta indicates? $S_{theta}(r)$ as we are saying that we are moving in a particular direction along the radial access; so thistells uswhat is the behavior of the spectrum along a radial direction from the origin.So, as we are moving in this particular direction and for this particular theta, we are computing this $S_{theta}(r)$, it tells us that what is the behavior of the spectrum along a radial direction as you move fromthe origin within the spectrum.

Similarly S_r theta, because this S_r theta is for a particular value of r; this indicates that what is thebehavior of the spectrum if I move along a circle of radius r centered at the origin.So, theseare the2 behaviors of the spectrum that can be obtained if I represent the Fourier spectrum in the polar coordinates.

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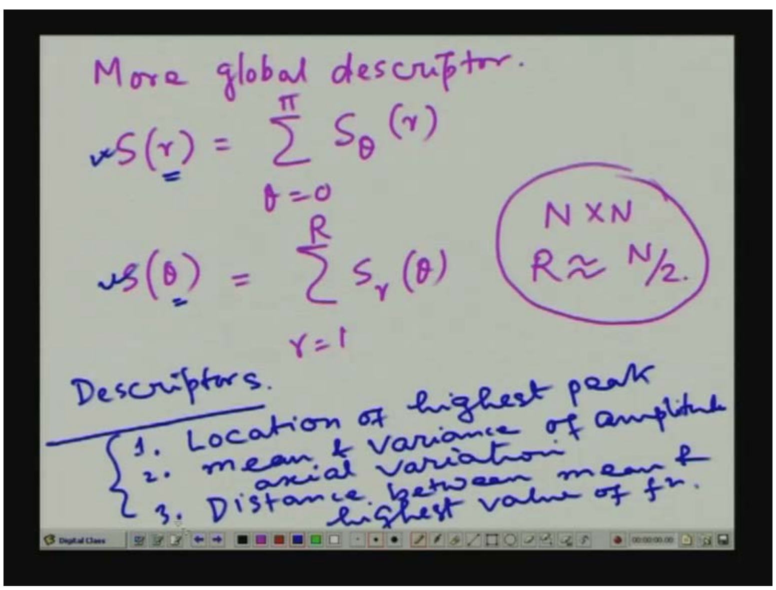

And,a more global descriptor can be obtained from these 2 functions.So, you can have more global descriptors which are given as S_r is equal to summation $S_{theta}(r)$ where you take the summation fromtheta equal to 0to pi and the other descriptor that we can obtain is S_{theta} which we have to take from S_r theta where this r will vary from say 1 to capital Rwhere this capital Ris relatedto dimension of the imageor similarly it is related to dimension of the Fourier spectral coefficients that we get.

Sonormally, if I have an image of size capital N by capital N, then value ofR is typically taken as capital N by 2.Sohere,you find that by varying the values of R and theta, R is the radial variable and theta is the angular variable.So, by varying the values ofthese R and theta,we can generatetwo1 dimensional functionswhich describe the texture energy content.So, if I vary the value R,I get one1 dimensional function which gives us an indication of the variation of the texture energy content as we move along the radial direction globally and if I vary the value of theta, this gives as the variation of the textural energy content as we move along the concentric circles within the spectral.

So, from these 2, the descriptors which are normally generatedis one kind of descriptor is the location of highest peak,the other kind ofdescriptor can be mean and varianceofamplitude as well as axial variation and which can also have the distancebetween mean andhighest value of the function.

So, these are the various descriptors that can be obtained from these 2 functions; S_r and S_{theta}. Now,what we mean by this?Letus take look at an example.

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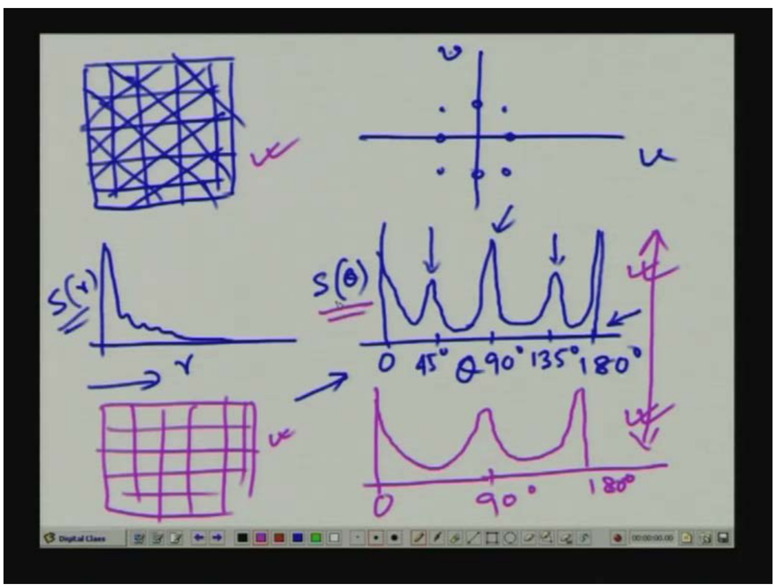

Suppose,I have a texture image which is given like this; so this shows atypical texture image.So, if I have a texture image of this form, you will find that in the frequency domain if in the Cartesian coordinated domain if I put it as uv,there are few horizontal lines and few vertical lines and for that I will have some spectral components in these difference locations.Similarly,there are diagonal lines which are oriented at 45 degreeand 135 degrees; so these are the pointswhich correspond to those diagonal patterns.

If I plot the S_r with r,a typical pattern of this S_r1 dimensional function of this is you can obtain something like this.So, it says that as we move radially from the center of the spectral plan, what we are doing is we are moving into more and more frequency components as it is quite obvious that in most of the images, we have higher energy content of higher low frequency energy content whereas lower, high frequency energy content and this is the typical pattern that we will get when we plot S_r versus r. Butwe get very very important information if I plot S (theta), S (theta)versus theta.

So, if I plot it from 0 to 180 degrees; so somewhere here we have 90 degrees, somewhere here we have 45 degrees, somewhere here we have 135 degrees and we will find that we will get a pattern something like this.So, it clearly shows that we have the periodic nature of the pattern in the horizontal direction with theta equal to 0, we have the strong periodic nature in the vertical direction that is theta is equal to 180and we also have sorry theta equal to 90 degree and we also have stranger periodic patterns in the 2 diagonal directions that is theta equal to 45 degree and theta equal to 135 degree.

Now, opposed to this if I have a texture pattern simply of this form,I have horizontal pattern and i have vertical pattern;so if I plot S (theta)versus theta of this particular texture pattern, that kind of plot that we will get is something like this.So, this is 180 degree, this is 90 degree and this is 0 degree.

So, hereyou will find that if I consider this S (theta)plot,from thisS theta plot,I can clearly demarcate between this texture and this kind of texture. So, this S (theta), this1 dimensional function provides very very important descriptor which can be used to describe texture as well as to discriminate among the textures and the various kinds ofdescriptors as we have said that the location of the peaks,similarly mean and varianceand also the distance of the highest value from the mean value; these are the different type of descriptors that can be obtained from this spectral domain.

So, till now what we have done is we have discussed about different descriptors, the shape descriptors, we have discussedabout the shape descriptors which are obtained from the boundary,the shape descriptors which are obtained from the region as well as the texture descriptors which are also region descriptors.

Now, for object classification or objectidentification,what we have to do is we have to make use of these descriptors.So, if I can assume that each of the descriptor to be a scalar quantity and each descriptor is a component of a particular vector;so if I put if I arrange different few of these descriptors in an ordered manner, what I can have is a vector representation of difference descriptors and these vector as we will see in our next class,we will call as feature vectors and based on the feature vectors, we can design some classifier or some recognizer using which we can recognize the object present in the image.

So,we will discuss about the object recognition or object understanding problems in our next class.Now, let us see some of the questions quiz questions from our today's lecture.

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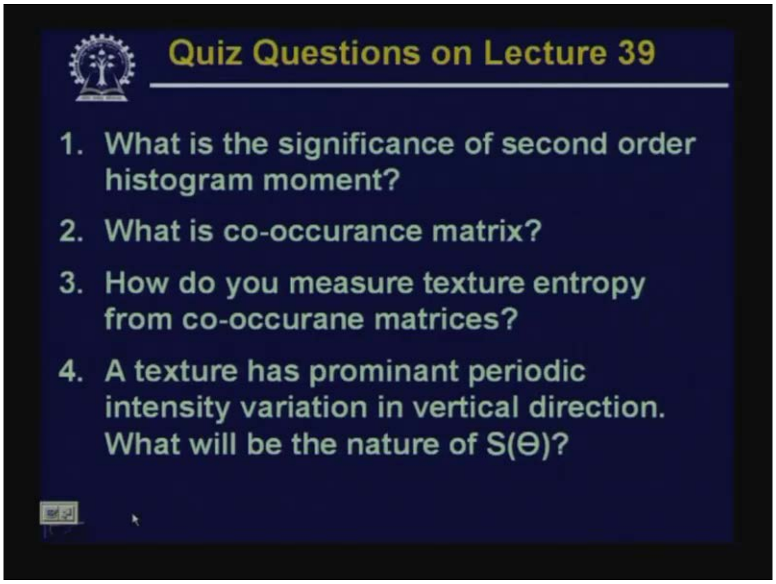

Thefirst question is what is the significance of second order histogram moment? The secondquestion, what is co-occurrence matrix? Third question, how do you measure texture entropy from co-occurrence matrices? The forth question, a texture has prominent periodic intensity variation in vertical direction; what will be the nature of S theta?

Thankyou.