Course on Introduction to Medical Imaging and Analysis Softwares
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Module 02
Lecture 06: Texture in Medical Images

So welcome to today's lecture on textures for dealing with medical images and what we will be discussing is quite interesting in terms because these are the first few elements we would be using for doing an actual image analysis. So we will start by dealing with what textures are and how they are defined and eventually we will go into different semantic categories of how textures are categorized over there along with the different measures for measuring different kinds of textures and eventually we will find an application area for them as well.

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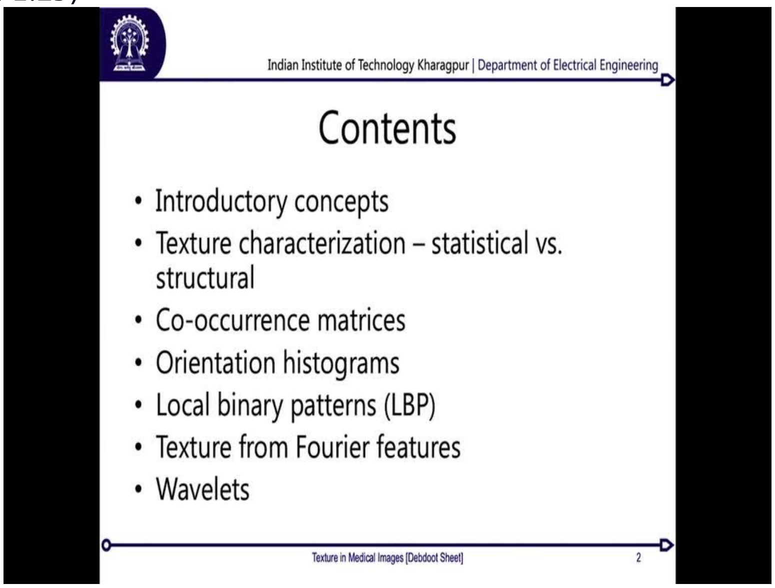

So without much of a delay over here let us start with so the first I will be introducing you the concepts about what textures are and try to at least elucidate as to what is the difference between texture which is quite a local phenomenon depended on the image appearance model itself versus what is noise which is also a local disturbance but that is not something which is dependent on the imaging which is not depended on the image parameter but is more of a function of the imaging instrument itself.

So from there I would go into telling into what statistical versus textural versus structural textures and what is the difference between each of them, how they are characterized independently of each other. Following that will be some of the very classical texture measures. So I will be starting with Co-occurrence matrices, Orientation histograms, Local binary patterns and textures from Fourier features and Wavelets. So we will be following one beyond the other in a very distinct fashion and each of them are pretty distinct of each other. So they are not quite overlapped as such and each of them reflect a very distinct property of the image itself.

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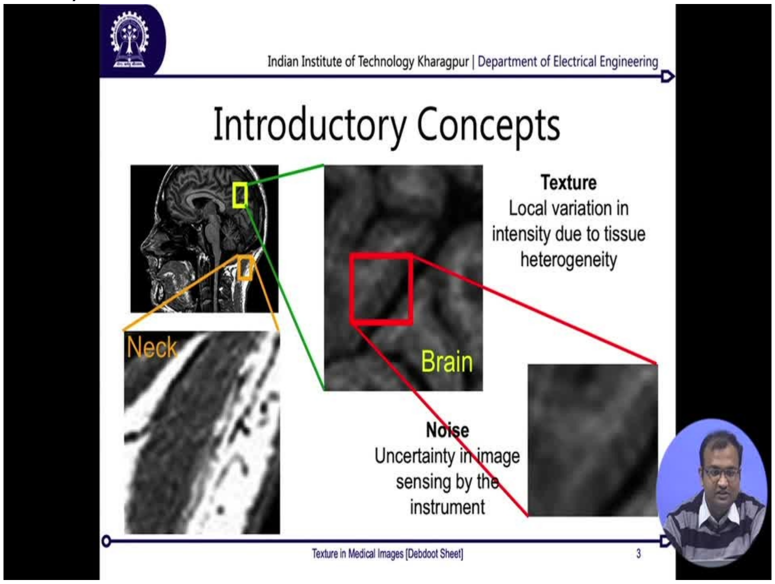

So let us come down to what they would mean. Say I am taking an MR image this is a T1 structural MR of the brain and if you look into this one over here you would be able to see some of the grey matter in terms of the brain matter over here, you would see the nasal cavity over here and from there you would see the oral cavity and here you would be able to see some of your spines and the rear part of your neck.

So the concept which comes down as to over here if you look carefully into each of them then you would see that locally they exhibit a different kind of a pattern which is not just a distinct grey level. So all of them share almost a similar kind of grey levels but then the amount of variation and how these variations happen locally is what makes it distinctly different from the others one over there.

So if you are looking at a part of a brain over there you would see that the kind of textures is where you have most of the part which is in white and then some parts you have these kind of black regions which are the regions and folds within your brain over there. And then if you consider and compare it with the part your neck the rear part of it, then we would see that the amount of grey level intensity the (av) average intensity over there is quite similar between each of them.

But then what makes it distinctly different is this is more of a texture less or something which is a very smoothened out area, whereas within the brain you would see that there are multiple number of folds kind of structure coming out over there. Now, this is what is defined as texture which is basically the local variation in intensity and which is due to the tissue heterogeneity present over there.

Now along with this one you can contrast another particular behavior which is called as noise and that is due to the uncertainty in the image sensing by the instruments, so if you zoom down much closer so basically noise and textures they in general appear at different scales of magnification. So while noise is something which would be corrupting each individual pixels over there and there would be variations if you look into per pixel level basis or much into closer into even at sub pixel level over there.

Whereas texture would be something which will be at a much more macro levels. So you need a group of pixels coming down over there in order to understand local variation between pixels such that you can characterize something called as a texture. Now let us go into a major part over there one is that we did not tell that your local variations and intensity is what will characterize the texture.

But the point is that since we have already learnt about different kind of imaging modalities some of them where your sensing mechanism is also stochastic in nature, so stochastic in nature means where your intensity also keeps on varying if you are looking across time or even on the local scale they would be varying. Now is there some sort of a distinct texture related to them as well is a major question which we need to address at this point of time.

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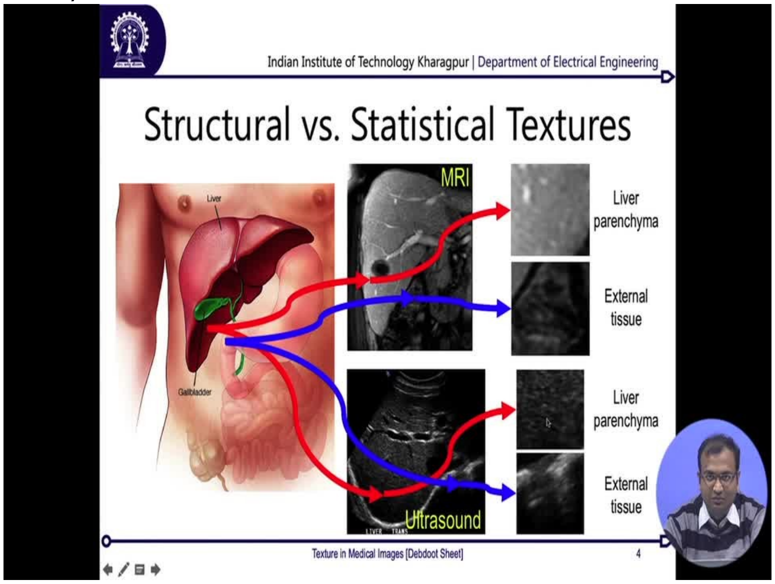

So that is where I would be bringing into this concept of what is a structural texture and what is a statistical texture. So let us take a the simple example of your liver and let us look into how you can scan the liver. So the first example which I take is basically to scan it with an MRI. So this is the same section of the liver which you are seeing on your MRI. So there is a small lesion which we see over here.

So they had not as of interest for this particular lecture but eventually we would be dealing much more details into what these lesions are and why they are more important when we come down to the case studies on the fourth week. Now say that I also have the same image of the liver being done with an ultrasound, okay. Now the challenge over here is that in your MRI of the liver you would see a very distinct intensity level over coming down, whereas in ultrasound you will not see such a distinct intensity level.

So let us basically magnify and look into one single region of interest, so if we look into the same region of interest which is within the liver parenchyma and you look into your MR over here and also look into your ultrasound over here. So in ultrasound image you would definitely see some local variations in intensities coming down, whereas in your MR image there is no such local variation of intensity visible, it is not such a great range.

You have some, so there are some of these white spots which are basically due to the hepatic blood vessels within your liver parenchyma, but it is not such as major change which you see whereas over here you would see that there are changes which happen almost like at a 2 or 3 pixel frequencies coming down in the spatial neighborhood. Now, let us compare the other two regions which are basically out of the liver parenchyma something within the body part over there.

So this is an external tissue if you look into the MR over there for this external tissue you see a distinct change in the grey level intensities and also in the nature of texture. So this part of it is quite highly textured the amount of high frequency components or local variations are much higher than compared to your liver parenchyma over there. It should be a very definite indicator saying that if it is a highly textured surface and it is not within the liver parenchyma as fa r as the T1 MR is concerned, whereas if it is not so textured then it is within the liver parenchyma.

Now the contra happens when you look in a ultrasound over here, the fun is that over here you would see that it is still quite full of speckles over there so you see lot of local variations. The only difference is that the nature of these speckles which appear in the external tissue is very different from the nature of speckles which appear within the liver parenchyma which is distinctly visible over here.

But the point is that if I am trying to use a structural approach to encoding textures which is say I am looking at just local variations and intensities over there. Then what I would be getting in the ultrasound for a liver parenchyma would be almost similar to what I would be getting for the external tissue in the ultrasound as well. Whereas, it would be very distinctly different if I am looking at an MR image. Now this is where you need to be very careful about choosing what kind of a descriptor you are going to use when you are going to segregate for each of them.

So descriptors for tissue characterization these descriptors for segmentation problems they are very much dependent on what kind of a modality you are using and what is the nature of local variations which distinctly guide that modality, whether you have a structural variation or whether you have a statistical variation on textures.

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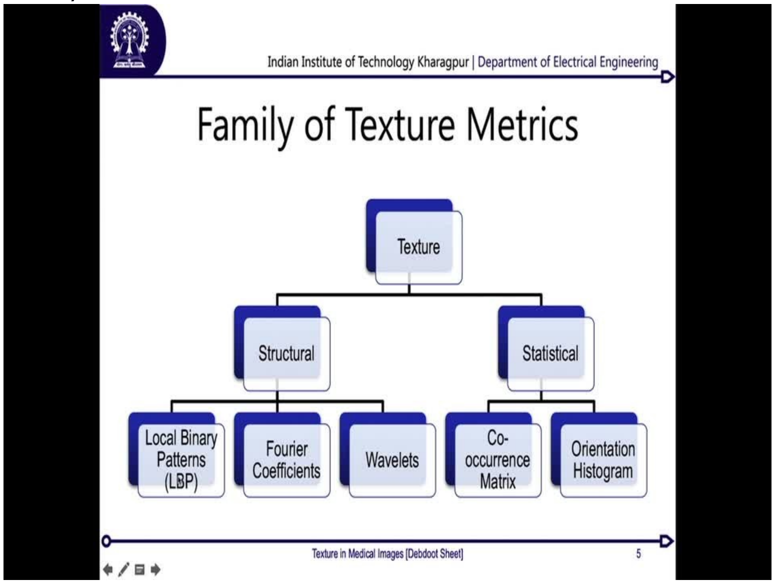

And that bring us to the point that we need to very clearly understand as to what are the family in which we can define them. So if you look at textures they are broadly classified as structural and statistical. So within the structural family the first one comes down a local binary pattern because it looks into the local variations over there, the next one is obviously Fourier coefficients which come down from the family of Fourier descriptors as well.

So this basically is something which you derive from Fourier coefficients and Fourier transform of an image. From there, the next one which comes is the wavelet coefficient and how these wavelets are used in order to define your textures. Now all of them and something which looks into the structure, the local structure and the variation across local structures.

The other part of it which is a statistical one looks into the total statistics, so one of them is a Orientation Histogram, the other is called as a Co-occurrence Matrix. They basically relay on the probability of joint occurrences between two different kind of intensities coming over there. As we go into them you will realize why this is called as statistical measure and not actually a structural measure.

We start with the most unique, the most recent one which happened in this history. So this is a particular contribution which is very recent in terms of based on 2006. And the amount of contribution it has the impact it has across the community is actually immensely large.

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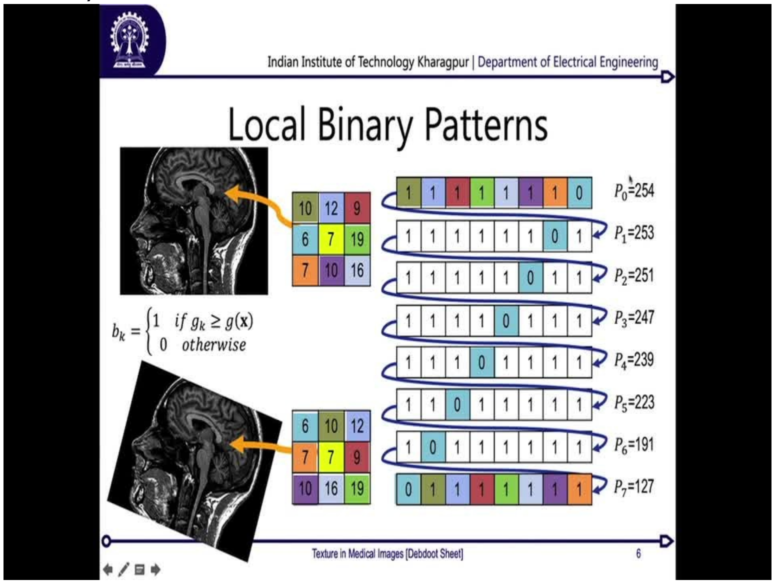

So let us look into this first family of descriptors which is called as Local Binary Pattern. So I start with very practical example, so say that I am looking at one particular location x and over there I consider a 3 cross 3 neighborhood around that location. Now, if this is what I observe on this 3 cross 3 location over there, so this at this particular point where this arrow head is pointing if you take a neighborhood of 3 cross 3, then this is the kind of structure you will be looking over there.

So, on this neighborhood the central pixel which is in yellow over here is actually the intensity present at that particular location x and all of these are its neighbors. Now these neighbors are basically encoded. So what we do is we generally follow a clockwise encoding scheme where you start with this particular location as the first element of this clockwise encoding and then you keep on following along this way to get down the rest of the elements.

Now, we define another sequence over here which is called as a binary coder. Now what this binary coder says is that this location is k equal to 0, this location is a k equal to 1. So the value over here is called as gk which is a grey intensity value, this central value over here is called as gx as in over here. So if the value of gk is greater than or equal to gx, then you substitute a binary code bk is equal to one otherwise you are going to put it down as 0.

So basically if you have the same value as the central pixel or a greater value you have a you say that it is true or the otherwise it is a logical false which you are going to substitute. Now from there what we can do is, we can efficiently generate a small pattern which will have 8 elements from this surrounding neighborhood which encodes into something like 8-bit integer number.

Now corresponding to this bit pattern since there are 8 elements over there, so obviously you can generate an integer coming out of it and say this one is called as if you have this sort of a pattern then obviously the value is 254, now great, it goes on good. Now one of the challenges which you face over here is pretty interesting, say that this person was rotated a bit, so every time you are not going to live quite outright straight into your MR machine and now you had just tilted your head a bit.

Now once you tilt your head a bit as such nothing in your anatomy or physiology is going to change, so if I am looking at the same location x again on this new image, I should be able to get its own neighborhood coming down over here, so this is what the neighborhood looks like. But now interestingly look over here that my k location for 0 which is this first location over here now got replaced by this number called as 6 intensity.

The next one got replaced by 10, so it is as if there has been a 45 degree tilt over here. So correspondingly if I try to generate the binary code over there this is what I would be getting down, okay. Now this comes down to a value of 127, now look into something quite interesting over here, you just tilted your head and the nature of texture which is supposed to come over here just that

Now this is something which can actually cause a great amount of trouble to most of the problems which we are trying to solve. Like there is not going to be solution, it is actually going to be a problem which is much more deeper in a sense itself. So now the question comes is there a way out? And apparently it looks like since you have a binary bit coding over there you can actually find out a way in order to make this rotation independent and how we do it is quite simple, so what you can do is that every time you get a byte code whenever you are generating this bit pattern over here, you can actually do a circular shift.

So you can do a circular right shift or you can do a circular left shift any one of them is possible so of now I am over here just doing a circular left shifting completely. Now if I do a circular left shift over there I would basically be able to generate 8 such possible variations of a code coming down, now once I generate 8 of these now one of these values will be uniquely the minimum value. So the maximum value is also going to be unique, the minimum value is also going to be unique.

So what we do over here is we just find out this minimum value out of this circular shift and say that that is basically the local binary pattern which is rotation invariant so this subscript RI is to denote that it is rotation invariant LBP at the particular location x and that is the minimum over all of this particular patterns which I can generate. So the idea is pretty simple that you have a structural texture descriptor over here which looks into local neighborhoods and it is quite immune to whatever kind of rotations local rotations you might ever have which makes it a very unique descriptor in its own way and the other good thing is since it is binary and you are just looking into greater than and less than comparison operations you can actually make it much faster than any of the texture descriptors (())(15:00).

Now from there from using this local binary pattern which is a quiet an intuitive and interesting one, so this does not only exist for 3 cross 3, you have literatures which say how to use it for larger neighborhoods, you can have a 5 cross 5, you can have 7 cross 7. And in fact since you would rather try to look into a circular neighborhood than how to extend them which are also present in literature, so you can look at that particular paper on local binary patterns and you can find it out, we will have the literature sedations at the end of the lecture slides where you have all the details. So they are something which are curiously interesting to be exploit expect for the fact that they are obviously computationally expensive on the other side of it.

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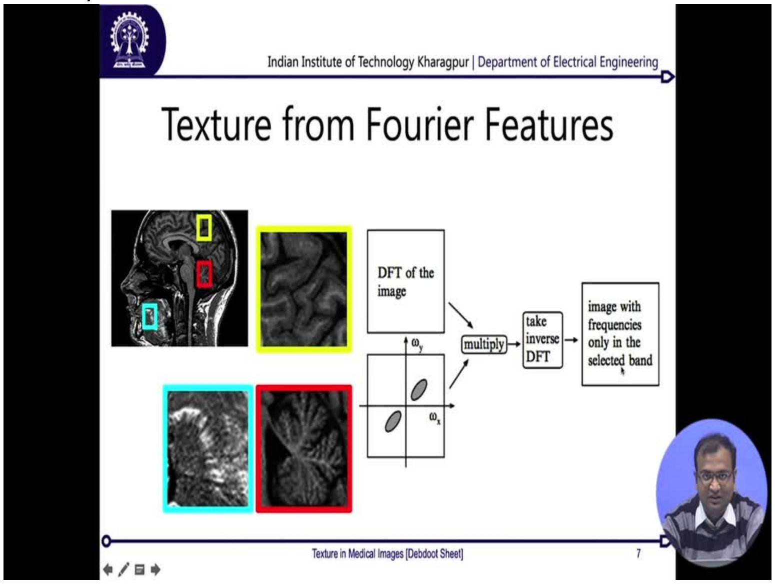

Now from there, we move on to another interesting one which is use your Fourier coefficients or Fourier features as a measure of texture. Now, one thing you might have noted is definitely that if you are looking at texture there is some sort of a regularity in terms of variations or your frequencies are quite so these variations they seem to have some sort of a spatial frequency. Now whenever the term spatial frequency comes into mind, one of the thing which definitely tickles our imagination is that why not think of dealing with frequency as one of the measures for using it.

And for that particular reason, we are going to use Fourier features as well in order to describe. Now let us take a sampler over there, let us take part of the brain which has this kind of an appearance. Let us take another sampler from this part which is just outside the brain and is one of the glands and look into that and let us take a part of our cavity within our mouth, so the oral cavity and look into each of them.

Now if you look at the frequencies over there, obviously the amount of folds and the ways the frequencies they are quite distinctly different there is some sort of a directed nature in this particular area, whereas over here it is quite undirected but the local variations are at a much lower frequency. If you look over here then these local variations sorry these local variations at a much higher frequency because they are very close to each other.

Whereas over here your local variations are at a much lower frequencies because they are very far apart from each other. Now from there what you can do is basically if you look into the DFT of each of these images, you can take small patches over there. So that would effectively mean in terms of your Fourier transform something equivalent to a short time Fourier transform. Over here it will be just be a short length Fourier transform or a patch wise DFT which we call.

And then, you can actually define different filters and these will just be some frequency band filters over there. Now in order to compute how to get these filters the best way is basically take multiple of these patches from one area and then you can take an average over all the DFT coefficients for all of those patches wherever you get your maxima locations, they are the most dominant frequency ranges.

And accordingly you can define these blobs which are the PAS regions and everything else is a 0 over here. You are just supposed to multiply that, take an inverse of the DFT and then you would be getting a region on the image which just shows you this part when it matches that particular frequency. So this is quite an intuitive way of very straight forward method for doing segmentation. The down side obviously is the computational complexity with a DFT because that is in the order of direct formation would be in the fourth order of the number of pixel you are taking down, fast Fourier transform would be in the square of the log of square of the number of pixel you are taking down.

So those computations are obviously a deterrent, other than that it is obviously a very good method for doing it if you have a lot of time in hand to spare in order to compute them. Now, since we have described these features which are called as Fourier features and how to look into them, there is obviously something which we should be exploring much more detail which is that now that I know that there is some (com) some aspect of spatial frequency involved in textures, then can I actually look into what spatial frequencies where generating those textures. So this is something similar to say Fourier spectral decomposition or a Fourier series decomposition which you would be taking in case of a signal.

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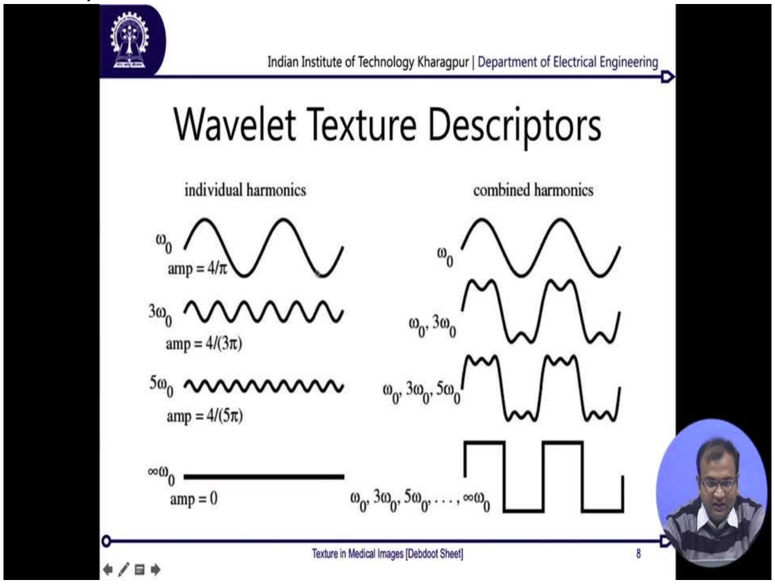

Now say that you had a signal and you had something basically a square wave and this is an experiment all of you would have done in your under graduate basics over there, so which was basically find out the coefficients and the amplitudes (ampli) coefficients are the amplitudes so find out the amplitudes and the frequencies of all the sinusoids which can be used in order to synthesis this square wave.

So from your experiments you remember that basically you need to have infinite number of amplitudes or all the possible harmonics which can go tending to infinity so that you have the best reconstruction. If you are taking something smaller than that you will have a jittery behavior over there, but you will be able to reconstruct almost something which looks like a square wave. Now and interestingly, if you take any of these frequencies and start correlating it with this square wave over there you will get a non-zero response, whereas you take a sub frequency in between these harmonics you will generally get a 0 correlation over there.

Now, correlation is basically a flipped out version of convolution, right this is what we all know from our understanding of signal processing and image processing which is fundamental to this course which we are doing. Now that is a curious case which we use over here. Now imagine that each of this wave is just a part of a wave and not a complete wave. Now, this particular one at omega 0 will be serving as a reference template in order to generate 3 omega 0.

So 3 omega not is generated by basically a compressing or fitting 3 times of the same wave into the same time length which is for omega not, simple definition, a 5 omega not is basically done by fitting 5 times the length of omega not into the same length as omega not, that is how you are going to generate multiple high harmonic frequencies over there. Now curiously, if this is the situation then why not let us look into waves which are not necessarily sinusoidal and think of it in this way that if there is a square wave and I want to represent it using some waves which are not sinusoidal but say square wave itself.

So if there is a square wave and I want to represent it using only just square waves and not sinusoidal coefficients and I define some sort of another integral transform which is not necessarily a Fourier transform but something like a square wave transform where the fundamental definition over there is every waves are square and then all harmonics are basically square the harmonics of that square waves coming down.

Now you would see that you would just need one square wave at the frequency omega not in order to synthesis this whole thing you do not need the other ones. So basically by changing the nature of the wave from a sine wave to a different kind of a wave you could cut down on the number of primal definition components you would need or the number of waves you would need over there in order to define.

And this is what is the basic understanding about wavelets. So wavelets are basically kind of structuring elements or they are sort of waves which are not necessarily sinusoidal but of some other definite quantity, the way they are defined can also be mathematically represented very explicitly and using these particular definitions you would be able to actually synthesis any sort of a structure over there.

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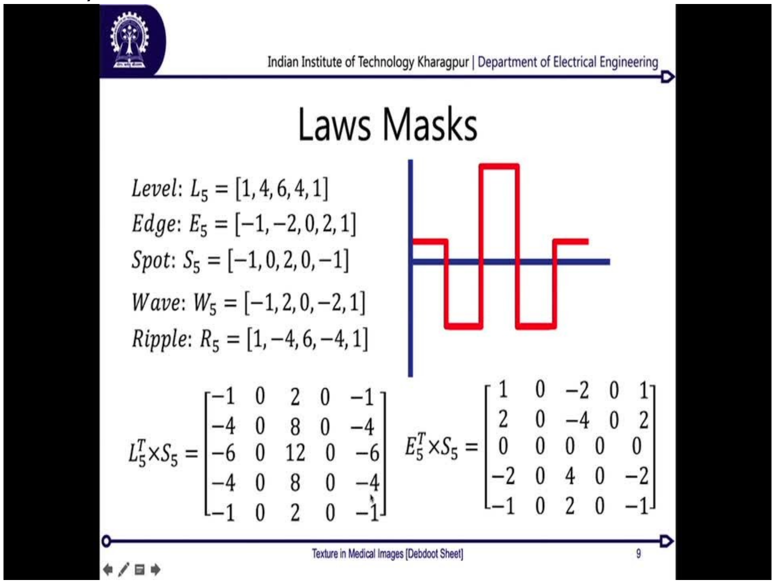

Now the first one we will come down is a very simple one and one of the most used and very simple to use one Laws Masks. Now I start with the 1d definition so that it is easier for you to understand. So let us what I have done is over here this is my y axis is my amplitude axis, the negative part and the positive part all balanced out and this line is my 0 line and this x axis is my sample number which would be coming down.

So the first wavelet in a laws mask is called as a level wavelet. We are looking at 5 element (()) (22:58) wavelet and that is why it is called as an L5. Now how it is defined since it is discrete you have distinct values specified over there and the values are something in the range of 1, 4, 6, 4, 1 and this is what the wavelet would look like if I am just going to plot it over there. Now from there consider that I am looking into another wavelet which is called as an edge, now this edge this is a kind of a formation which you would look into them.

Now why they get their names are very distinctly interesting because if you look into this particular kind of a wavelet and you convolve this with another function where you have level shifts then it is going to give you a very high response whenever you encounter a level shift in your intensities over there. If you are looking into edge, then you would see that this replicates very much differential operator or derivative operator, so whenever there are edges you get a very high response coming out at that region.

This is a spot operator which is something which is if you have a very high impulse coming down and a correlation is going to give you very high result over there. For a flat region it is going to give you a 0 response because the total sum total over this whole thing comes out (()) (24:04). Now from there the other one is called as a Wave. So this is in a nature of as if you have a sine wave and then what will be the response coming down over there.

From there the other one is Ripple which is very similar to a laplacian of Gaussian or the second order derivative over the whole image. Now from these all of these wavelets are basically defined along one axis but for us our images do not exist in one single axis, they exist in 2 different axis, right? It is an x axis and a y axis and for medical images where you also have a z stacking available you would be having images which exist in all the five axis all the three axis itself. .

Now the question comes is can we synthesis higher order filters say a squared filter from using these 1d masks over there and that is actually very simple, what you can do is you can take a outer product so take a transpose of one of them and do a cross product with the other one of them. So you can very well take a level transformation on the x axis and the y axis together you can take a level transformation on the x axis and you can take a spot transformation on the y axis.

Now together what you will do is if you just do a cross product over there you would get a square matrix which too looks something like this. Now the very easy thing is that if I want to sense if there is a level transformation along the x axis and though spot exist along the y axis, so what I need to do is basically use these particular matrix as a convolution kernel and just convolve with the image.

So at all of those positions where I get a high response, that is where you have a level transformation in the x axis and the spot transformation in the y axis coming down. Similarly I can define another filter kernel as well and this kind of a kernel is basically E5T which is my edge on the x axis and my spot on the y axis. So you can since you have 5 primal component elements over there you basically have an option of synthesizing 25 such filters over there.

Now all of these filters together is what is called as the filter bank. Each of this is called as one of the wavelets or the mother wavelet for the rest of the filter bank over there. Now laws masks is not necessarily restricted to only just 5 elements or a 5 cross 5 dimension, you have them in 3 cross 3 as well you can extend them to 7 elements, 9 elements, 11 elements. So later on as we have all the books over there I will be showing you as to how to expand and what to do.

So you can read through much more details in the text books which are referred over there for more of the details. Now, if you clearly look into this one you would see that one point is that all of them are integer kind of wavelets, you have levels in which it is translating it is not a continuous function in which the translation happens.

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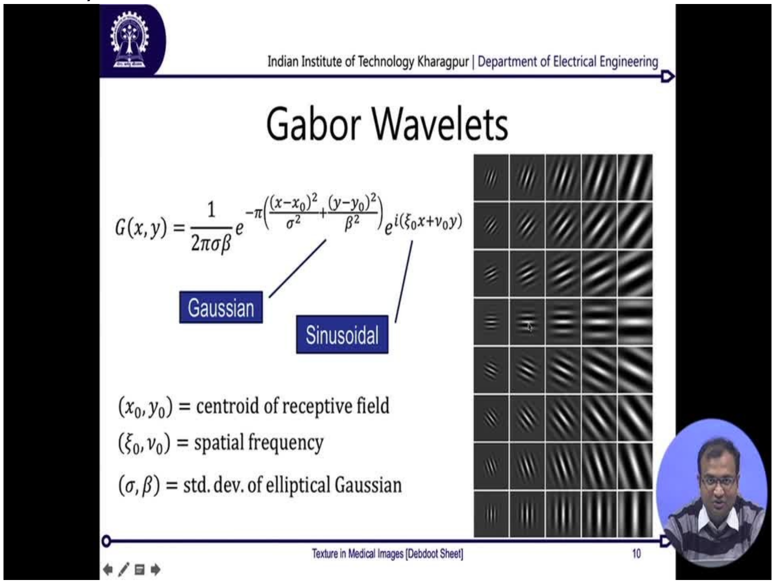

Now for that a much more improvised kind of a wavelet is called as a Gabor wavelet. Now over here if you look there a lot of exponentials basically but there is nothing to be confused over there because the first exponential over here is something which defines a Gaussian. So it is an e power of minus pi and there is a x square by sigma square y square by beta square. And on the other side of it is this exponential which also has a complex quantity i.

Now if there is a e to the power of i theta, by definition we know that from the (())(27:22) expansion you would get a sine theta and a cos theta term over this so there is definitely something which is similar to a wave. Now this part is interesting because this gives you the Fourier fundamental frequencies and this gives you a damping over the fundamental frequencies, so now you just do not have a Fourier wave but you also have a amplitude envelope on top of the Fourier wave together going down.

And everything balanced out so is that energy over the whole envelope stays still restricted to 1. Now x not and y not is basically called as the centroid of the receptive field or basically the centroid location on which pixel you are going to operate this whole thing and zeta not and nu not are called as the spatial frequencies so zeta not is the spatial frequency along x, nu not is the spatial frequency along the y axis, alpha's and beta's are the elliptical standard deviation of this elliptical Gaussian over there.

So if you want to take non elliptical Gaussian you can put down a circular Gaussian then you can put down sigma is equal to beta into as some particular number. Now this is an example of how these wavelets look like. So as you keep on varying the so we specifically take down sigma equal to beta equal to the same number and this is the variation of this sigma and the beta range which is if I am looking along the x axis then everything is varying in terms of my standard deviation of the Gaussian.

If I am looking along my y axis then what I am basically varying is the frequency zeta not and nu not, so as the frequency zeta not and nu not so over here you would see that this wavelet is perfectly aligned along the y axis but the x axis there is no frequency present over there. Whereas if you look into this one and this one, you would see that the whole frequency exists along the x axis, there is no frequency which is existing along the y axis.

And intermediate you would see all of these variations, so by basically changing these parameters over there I can generate a whole family of multiple of these coming down and each of them is called as wavelet element of this whole family over there and this is the mother wavelet which defines the every element of that family. So these were what we call as structural measures for understanding structural textures. So this is one family which just ends over there and in the same way you have you can use it is for any wavelet, so you would just be convolving one of them and doing it.

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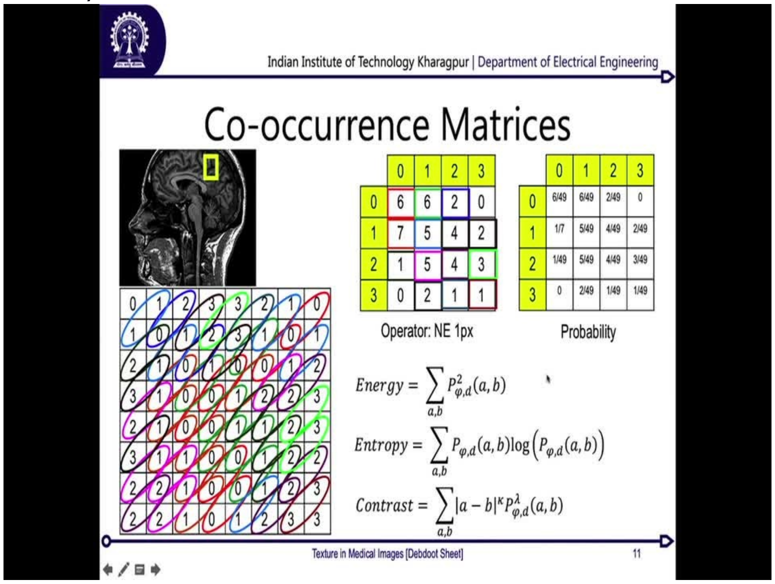

But the other one which we are entering down which is called as the statistical measure, so first I will be dealing with Co-occurrence Matrices. This does not use make use of anything from a linear space in variant system or no concepts over there, there is no convolution evolve or anything. Now this is purely something based on spot counting, techniques would be similar to what you have done on your local binary patterns over there, so we need to again look into one spot and look into its neighborhood and then we are going to count down the number of elements over there.

And as the name suggests Co-occurrence so this means that two object need to occur simultaneously together and we are just going to measure how simultaneity is present between their there occurrences. So let us look at one particular region, this small region over here. So this is a small 8 cross 8 region which I am looking down over here and this is the kind of intensities which I would be seeing on this 8 cross 8 region.

Now from there let us take an operator which is called as a north east 1 pixel pointing, so what that means is basically if you are standing at one particular pixel location say this particular location, you need to take an operator which will related this particular pixel location to this location. So that is my north east and there is a 1 pixel, so say that I if I use a 2 pixel north east pointer so that will be something I look at this pixel and I am going to look at what is the relation between this pixel and this pixel and there is nothing to be included for this pixel or any other pixel over there. So that would be a north east 2 pixel.

If I say that I am north with 1 pixel so it is basically look into this pixel and look into this pixel, their occurrence together, but remember one thing in mind, these operators are very much directive and direction sensitive. So if you have a north one pixel which means from here I am looking over here there is no way that I am going to look in the reverse down because the reverse way will basically be a south 1 pixel pointing operator over there.

Now with this one let us start how the whole thing is done, so how this matrix is defined is first I will be looking into all the possible grey values. Now over here if you look into this particular table you would see that the intensity value is exist in the range of 0 to 3. So definitely this is encoded in a 2-bit number. that is why you have just existing between 0 and 3. So we point down this particular side of it which is all the rows are arranged at the first element which I am looking at.

And these columns are arranged based on the second element to which it is pointing and I am looking over there. Now let us start by counting, so if x is 0 and the pixel towards it is north east is also 0 and let us see how many of them are there, so you can distinctly count down that there is 6 or such occurring over there, so it gets filled up with 6. The next one is my central pixel is 0 and it is pointing to a north east pixel which has a value of 1. Also interestingly find out that there are also 6 such combinations over there.

Now for the next one I have a central pixel of 0 and it points down to an intensity value of 2, so there are two such occurrences where you would be looking into it. For here we do not have any of them. In this case where it is number of times there is a central pixel value of 1 and it points to a 0, there are seven of them and eventually you keep on looking into all of those possible combinations and you can trace out those particular pairs coming down in your image and you can populate the whole table over there.

Now it might sometimes happen that most of your table will basically return down a 0 value over there which is pretty common and there is nothing to be worried about it. In fact there is something where you can say that it will be texture less. We will come down to the specific case when it is called as a texture less based on this one. So once you have done all of this, now what you can do is, this whole table is basically a 2d histogram which you have over there of co-occurrences.

Now from a histogram I can definitely generate my probability now. Now the sum total of all the elements in this histogram is basically equal to 49. Now that also has a relation to this whole size of the image on which I am looking at. Now how this is defined as see if I am looking at a north east pixel pointing down, so basically my all x locations they can vary from here to here this particular will not be taken into consider because I do not have a valid existence.

So there are seven such rows which can be taken care of and if I vary along this axis I will just get seven such possible columns over which I can actually compute it out. So there will basically be a valid region of this one which is 7 cross 7 or total 49 elements over where I can count out. So always remember that sum total of this histogram should be 49, if it is not then you need to really revise there is possible some amount of pairs which you have forgot to taken down over there, so that is a trick to understanding whether your co-occurrence matrix is perfectly populated or not.

Now from there since we have this probability and obviously the sum total of this probability table is going to be 1 by definition of probability. We can found find out a few interesting measures, one of them is energy which is defined as square of the probability, a and b is basically this combination 0 and 0 is a, b here for this particular 0, 1 is a, b 5 is basically the direction at which you are pointing, so over here it is north east and d over here is basically the distance over which you are going to look into, so that is 1 pixel.

For entropy it is a standard definition except for it is over a pair of a’s and b’s which you look over here because it is a 2d histogram. And interesting one is contrast so this is a very interesting measure from the point that you can actually measure whether your image has a high contrast or it has a low contrast or 0 contrast. Now this whole thing would end up becoming 0 if everything is flat, say all the values over here are of every everything within this patch is 1’s all 1’s. Than what you have is a minus b will be 1 minus 1 and for that you will have a probability of 1, but 1 minus 1 raised to any power kappa will make it 0, that is why you have a contrast of 0, so a flat image basically has a contrast of 0.

Now similarly you can measure whether you are on a flat image or you are not on a flat image using these kind of things or whether you are on a highly textured image or not on a highly textured image. So if your entropy is basically 0 than again you are on a flat image, if your entropy is something which is much closer to 1 when you are something which is like on a highly textured out image itself.

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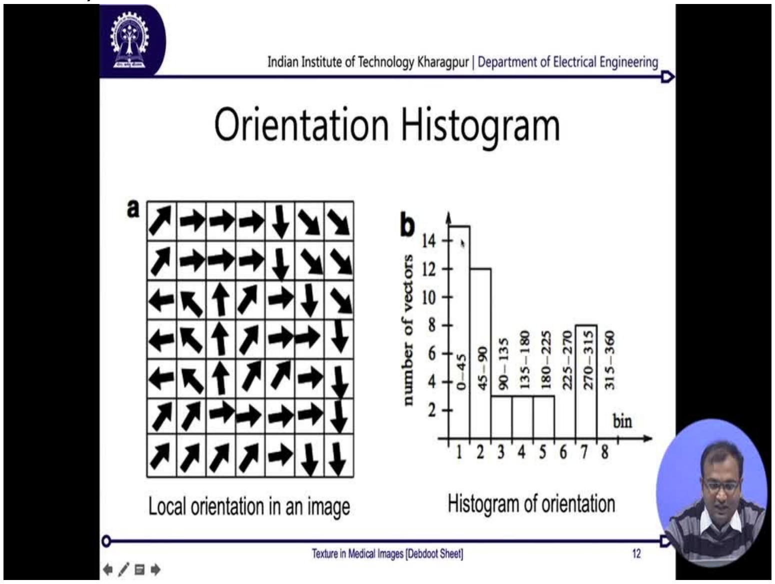

Now from there another short and quick introduction is on orientation histogram. Now what it does is you all know about these gradient operators and edge operators say using a soble and everything. Now on the soble you were finding out the magnitude but you can always find out the gradient as well, so you basically take a tan inverse of y gradient and the x gradient, so you will get down an direction in which that particular gradient is pointing over there.

Now say that you are looking at each pixel over there and then you find out what is the gradient around all of that pixels and then you populate that into one particular matrix which is called as a local orientations in an image. Now from that orientation you can basically create a histogram which is of orientations over there which is called as a histogram of oriented gradients itself. So basically you look into which direction your gradients are oriented and you look over here. Now interestingly what will happen is this histogram will be unimodal if everything is oriented along one direction.

Now if everything is chaotic and all edges are oriented along different directions so you will have a very flat histogram over here, so all possible gradients will have the same probability over there. So over here we look into this particular kind of histogram which comes out for this particular kind of an orientation. Now these are quite interesting in order to understand whether your textures are directed or undirected so whether you are looking at fibrous bundles or you are looking at some scattered passes of tissues.

So when we come down to more of those case studies you will see a practical application where these will be used further as well.

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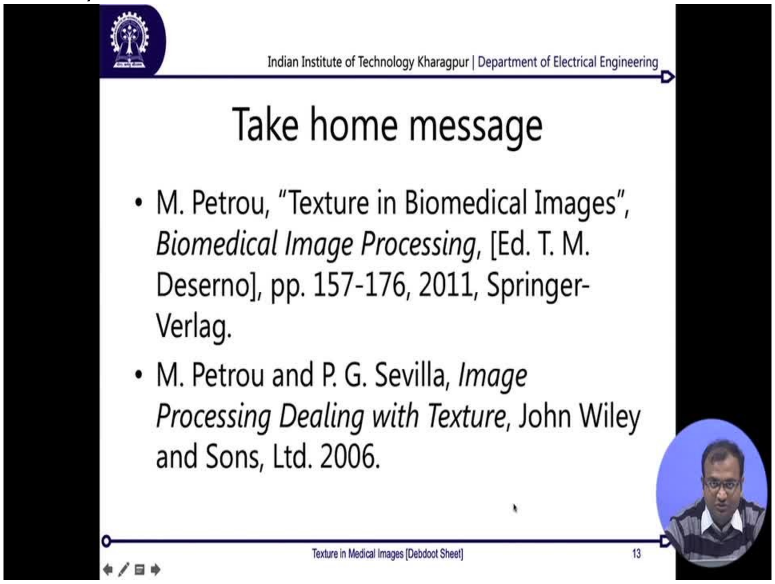

So from there we are actually at the end of today's lecture, so the take home message is that you can actually look into these two books for more of details. So the first book is the first is basically a book chapter on biomedical image processing, a good review of all different measures and the second one is a complete text a full major volume text on multiple ways of handling textures and different kind of texture measures which you can use, so these are two defiant reads I would recommend for much more detailing as well, so with that thank you.