Introduction to Medical Imaging and Analysis Softwares
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Module 4
Lecture No 17
Vessel Segmentation in Computed Tomography Sean of Lungs

So welcome to today's session and what I am going to discuss is another application area and likewise that you have already read about in the previous lecture on retinal image analysis and vessel segmentation within retina. So I am going on to extend onto this one because vessels are also found in other organs of the body and one of those particular organ which we are going to take is lungs and I am going to discuss about vessel segmentation in lung.

And for a specific purpose we are going to stick down only to computer tomography scans in the lungs for this purpose and not any other of them. Now, one major reason why CT is being taken over here is that lung is that one of those predominant organs which is radio logically image, so which means that you use some sort of an X-ray for imaging, although MR is also one of the possibilities but since it is quite fill full of air over there in majority.

So such MR would not be giving you that kind of a contrast difference between the soft tissues and blood beryl levels which is expected over there. Whereas if you look at CT over there you would get down a pretty much contrastive difference between the flowing blood to the alveolar air pockets over there. So what we would be having is it organized as where I would be introducing to you to one of the challenge which was there in (()) (1:42) sometime back and this whole challenge was about vessel segmentation in lungs.

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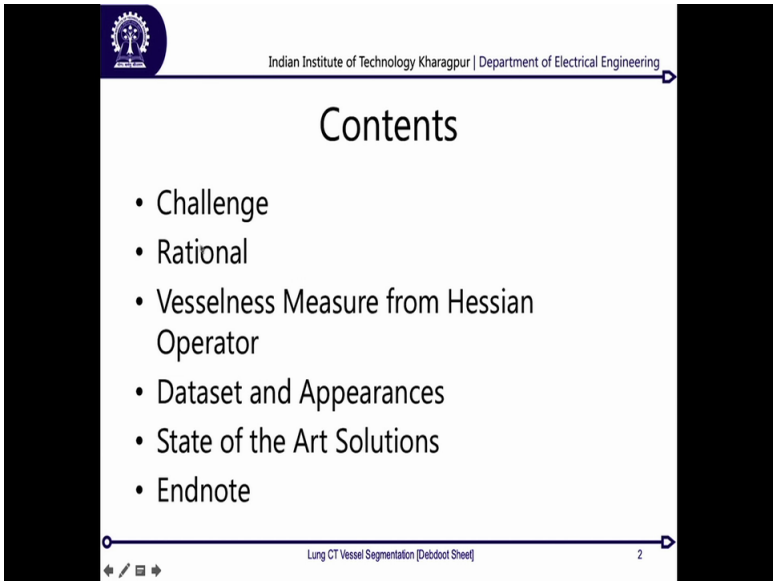

And the rational is so that you get to know more about the papers and a standard dataset which is used in this particular field of lung vessel segmentation. So from there I would enter into what is a clinical rational and use of having done a lung vessel segmentation, with that I would enter into something called as a vesselness measure invented by Alejandro Frangi and this is one of those seminal papers which gives you a clear idea about in the early days how people had actually worked out onto segment out vessels in 3D.

And this this paper dates back way to back to the early 1990s and at that point of time there was not any machine learning based techniques as we know today for segmentation in 3D objects, but we did figure out a way of using hessian based operators and then finding out principle component analysis and the principle component vectors over there in order to figure out how we can find out a vesselness response.

So that was one major thing as a prior art contribution and one of the strongest endings at points from the prospective of vessel segmentation. From there I would enter into describing this particular dataset on the challenge, which we are speaking about and the different appearances of vessels as you would see either on slices or on total volumes. And even trying to make you aware about what all different kind of ambiguities may arise if they were accidently arise.

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So from there we have a tabular comparison of state of the art solutions from the paper which was published on this particular challenge and with that I would come down to an end note with a reference to the paper about which I am discussing. Now, let us enter into what this challenge is all about so it is called as a vessel 2012 challenge and you can find it out grand challenges, so this is the URL where you can point it down and if you look careful over there it is called as a vessel segmentation in lung 2012 and this was held at ISBI 2012 for the purpose.

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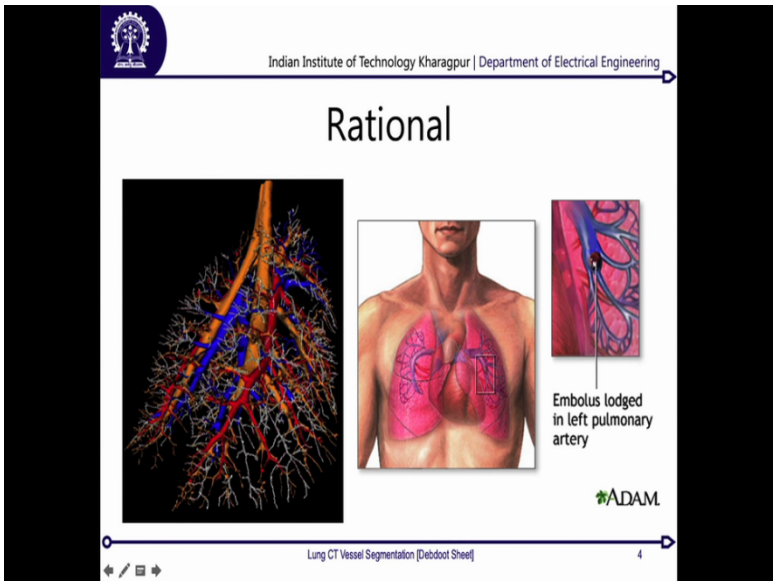

Now the rational which goes down is somewhat like this so on my left over here if you see, you have lot of this colorful network structure kind of thing going down and these blue ones

are the ones which are colored down and they are the main veins from which your blood flows out and this red one are the main arteries through which your blood flows into the lungs and this orange color is the areolar pathway. So this is where air tract goes in and then it moves into the alveolus within your lungs, so they are small balloon like structures around which you have blood capillaries going down such that there is gaseous diffusion taking place and that is how your blood gets oxygenated within the lungs.

Now, what we want to do is somewhat segment out these kinds of structures over there. So there can be vascular structure as in blood vessels, there can also be airway structures which are also tubular in its appearance model. Now the reason why we need to do all of them is one of one of this condition which is called as pulmonary embolism and what happens in this case is that if you look carefully then say I have a bottle of water over here with me and then I shake it quite much.

So you would see that there would be some sort of a bubble formation over there this gas gets mixed over there. Now this happens when this whole thing over here is a perfectly sort of Newtonian fluid which means it is not compressible as such. Now if you consider blood then that is not something which is Newtonian and you can compress blood, it does not have a viscous flow over there and then so there are other properties over there.

Now, if you have this gaseous diffusion exchange going down over there and there it goes down into a turbulence which generally happens when it is flowing within a ventricles and auricles of your heart, then you would be having a small gaseous bubbles being formed and the same way as I had done with this water bottle over here. Now those gaseous bubbles often they might get lodged over here into this blockage of this.

So whenever there are small arterials or capillaries which are branching out from arteries or there are venules over there, so this gas bubble might get lodged over there and then it will restrict flow of any blood through these thin capillaries. Now you need to be able to detect whether there has been this kind of a blockage and once this kind of a thing happens what happens is that you have another secondary phenomena which is called as aneurysm development and that means that there would be new arteries which just keep on branching from this blocked out parts, so that it can find out a way in which the blood can flow.

Then that would form down sort of a small ball a furry ball like structure of lot of arteries wriggling here and there and it forms a total mass, which is not supposed to be present in a

perfectly healthy situation of the human being over there. Now for this particular reason we need to be able to find out along these arteries where all suddenly there are these aneurysm formations and everything.

And that would mean that from looking into the CT image there has to be some way of finding looking through across each and every vessel along the length, so if there are vascular tree, so say this is a major vessel coming up and then you have it divided into two different trees and then I will have to track it along the length in order to find out where all it suddenly stop and you had say a possibility of having an aneurysm.

So that would and if you look carefully at this particular structure you see that there are many arteries, there are so many vessels which can be present over here. So in order to find that there has to be some way to isolate and associate them on the 3D space. Now this is the challenge which we are trying to solve by medical image analysis. So there are millions of such capillaries, veins, arteries and all sorts of vessels, which are present over there and you would like to track and segment out practically each of them which is not so easy to be done manually as such.

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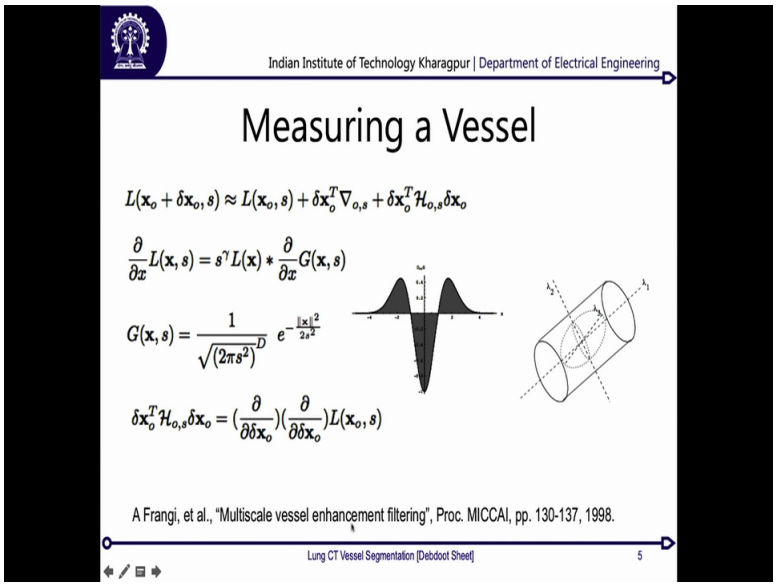

Now for that is when this particular paper by Frangi was on the MICCAI proceedings in 1998 and this is what it solves. So let us go down to the basic equations I will give you a small walk through about what that means, the first equation over here is basically a representation of what the image would look like, so L is typically called as the image intensity over there and this intensity is at a location x not.

So this x is bold, so it is a vector location, so it can be if you are considering a 2D space then this is a x, y coordinates space, if you are considering a 3D space then it is x, y, z, so you have a tuple representation coming down. And delta x is just a small shift variation over there and s is what is called as the scale. Now from where this scale comes down is say you have a whole volume taken down say I am taking a complete volume, which is about 30 centimeters cross 30 centimeters cross 30 centimeters.

Now on the digital space when I am digitizing say I am digitizing this into 512 cross 512 cross 512, this is one way in which my resolution would fall down to 30 centimeters divided by 512, this is my resolution along each dimension of space. Now, I can also represent it in lower number of voxels, say 256 cross 256 cross 256, in that case my resolution or the minimum resolvability that length is going to increase. So earlier I had 30 centimeters divided by 512, now I have 30 centimeters divided by 256, so the smallest size of the object which I could see in the earlier case is almost half smaller than the object which I can see in the latter case which had just 256 samples over there. Now this appearance model of all of these objects will always be changing with the number of samples I keep on pooling and that is a factor which is called as s for us ok.

Now if you have this kind of a way then you follow down a Taylor series expansion. So since there is a x + delta x, so you can always do a expansion on the Taylor series and that would have some sort of a factors over there, one of them is this gradient factor and the other factor this age is what is called as the hessian factor over there.

Now this hessian is something which you can associate very closely with the laplacian, so a laplacian matrix is basically in a laplacian what you have, say for a 3D case you have a del2 del x2 + del2 del y2 + del2 del z2, ok this is what you would have for a laplacian in a 3D case, in case of a hessian what you would have is since you have 2 different vertices along which you are going to compute, so I will have all of the other factors coming down which is del del y of del del x, I will also have del del x of del del y, then a del del x of del del z, then a del del z of del del y and a del del z of del del x as well. Along with that I have a del del z of del del z which would make it down as del2delz2, right.

So if I am taking all of them together that is matrix which is called as a hessian matrix, on a 2D case this matrix would just be a 2D operator matrix, in a 3D case this becomes a some sort of a, so in a 2D case you just have a 2 cross 2 operator matrix, in case of a 3D case you will have a 3 by 3 operator matrix coming down over here.

Now from that let us look into the first derivative of the image itself at a particular location. So what I can express this one at a given scale is that I take this to the power of gamma and then the derivate of this one will basically this scale factor to the power of gamma and gamma is a particular constraint factor on which we are going to work out, times multiplied by the actual scale by the image at the native scale which is scale s equal to 0 and then you take that convolute with a derivate of a Gaussian kernel.

This is what this first factor over here looks like, such that this G is a Gaussian kernel which you have over (()) (12:16) now solving all of these together what you would end up getting is that this hessian, which you see over here this has this sort of an expansion form, ok. So in a sense, what would come out is a factor which we are looking something like this, say that there is a cylindrical structures.

So your blood vessels which on the 3D space they are obviously in a small piece of volume if you see, you would see a piece of cylinder, ok. Now if I am travelling along the length of a vessel, then I would just be seeing these cylinders going down along the length of the vessel those small vessels. Now I take one small volume over there in which I will be getting a piece wise cylinder, now on piece wise cylinder if I am going to take a derivate along the length of the cylinder then I will get this sort of a pattern my for my second round derivate which is very similar to your actual pattern of a laplacian of Gaussian, ok, so this is a concept which we use from here and then we extend on to that concept.

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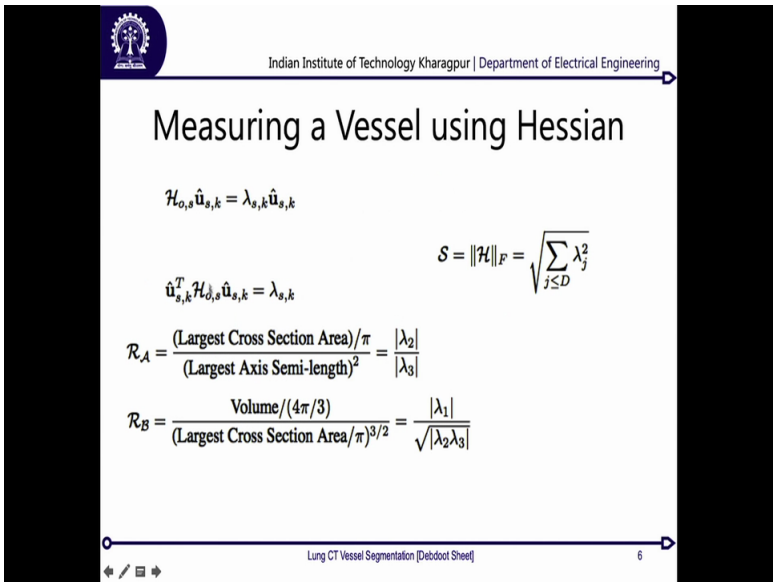

So what we do is now we run down an Eigen-value decomposition or a say a principle component analysis on the hessian response of this hessian response on the image such that we say that this hessian response on the image is equal to some sort of a lambda times, where these lambdas are the principle component magnitudes time this principle component vectors over there.

So that you can get down by just doing a principle component analysis, now we are not interested much of in the vectors, so these vectors would basically be aligned along these direction, so you would have one say over here, another over here and another somewhere in between. This was a perfect cylinder, but if you have a curve cylinder then you will have some different sort of an, say if you have so what would happen is that these axis would no more be aligned along the x, y or z axis, but they will be aligned along the length and then your cylinder is going to change along the length and accordingly your these unity vectors will also be changing.

But what we are more of interested is in the magnitude of this eigenvector, which is my lambda factor. Now from that what these authors had derived out was, they found a 2 different coefficients called as RA and RB, ok. Now RA is basically called as the ratio between the largest cross sectional areas to the largest semi to the largest axis semi-length. So largest cross sectional area means that if I have a cylinder over there and I chop it off so what will be the total cross sectional area and my largest axis semi-length means, if I assume that this cylinder is a finite cylinder then I will have my largest axis which is along the axis over there, so what is the half of that length.

So that comes down as just the ratio between this amplitudes of these 2 vectors, the second eigenvector and the third eigenvector, the value of the eigenvector sorry, so it becomes as the ratio between the second eigenvalue and the third. The next one is what gives a ratio between the volume of that total cylinder to the largest cross sectional area and that is given down by the ratio between the first eigenvector to the root over the second and the product of second and third eigenvectors over there.

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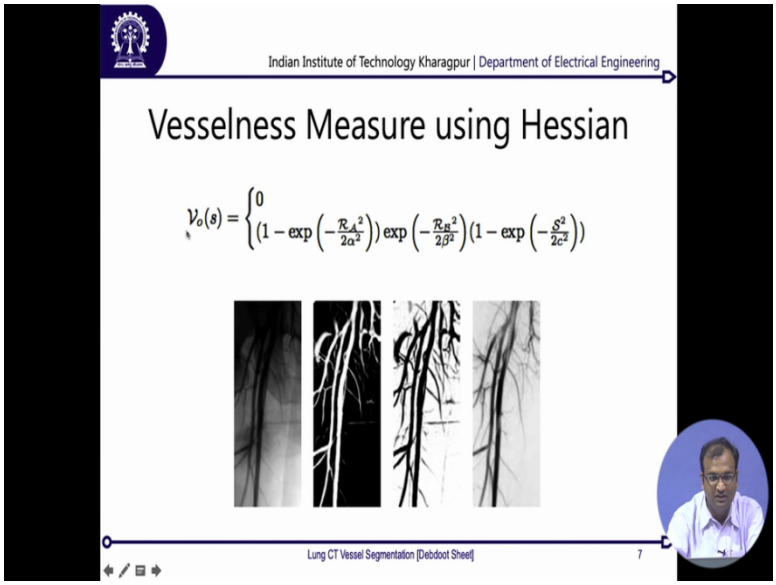

Now you can go for much more details into this paper and find out the theoretical deductions behind them. Now, where we end up using that is somewhere over here which we called as the vesselness measure, so this vesselness measure is a function which is defined as using those factors called as RA and RB and this other factor called as S which we had computed here which is basically the absolute summation over all the eigenvectors all the eigenvalues which you find it out.

Now, using all of this what we end up getting is a vessel enhancing filter, so if you carefully look over here this is a coronary angiogram or an X-ray taken down when there was a contrast dye injected into your blood stream. So because of this radiopaque contrast dye in your blood stream so you get them as dark and everything else is bright, but the problem is if you look into this sort of an image here there is a lot of intensity inhomogeneity this side it is quite bright in the background, over here it is quite dark.

So over here the vessels are pretty easily discriminable but here as you go it is really hard for you to find out where these vessels are, but using this kind of a filter you would be able to very easily get down a vessel map against a black background. And this is just opposite of this particular vessel map which I am seeing over there. Now using these two factors you can obviously correct for the intensity inhomogeneity over here and then you can find out this sort of an image, so what it would do is essentially it would subtract out everything on the background other than the vessels kept in the raw intensity. And now what I get is a

angiogram image or a map of all the vessels in its original form without the inhomogeneity in the background intensity at all.

Now this is what a very simple technique which was not using any sort of complicated algorithms on say convex optimizations, or neural networks, or random forests or Bayesian belief networks or any of them to do it. And it was just a pure voxel to voxel calculation finding out a hessian of the whole volume for each point from the hessian matrix you find out the 3 eigenvalues and eigenvectors you use just those eigenvalues in order to compute three factors RA, RB and S.

And given down you have three constraint coefficients which you tune as per your application as alpha, beta and c. You can always create out this wonderful vessel segmentation coming down and it is a, you do not need any learning samples, you do not have Bayes variations across different imaging instruments except for this tunablity of alphas and betas and Cs, which you will have to do appropriately.

Now with these this has been a state of art for long, so since 1998 till 2012, when this challenge got announced this was the state of art but once the challenge got announced what they did was quite interesting. So since we have this problem of changing across vendors and changing across hospitals, so imaging instruments as they keep on changing their resolution changes, their operating behaviors changes and as a result all of your image analysis problems which got trained on one domain in order to make it work on another domain becomes a major challenge.

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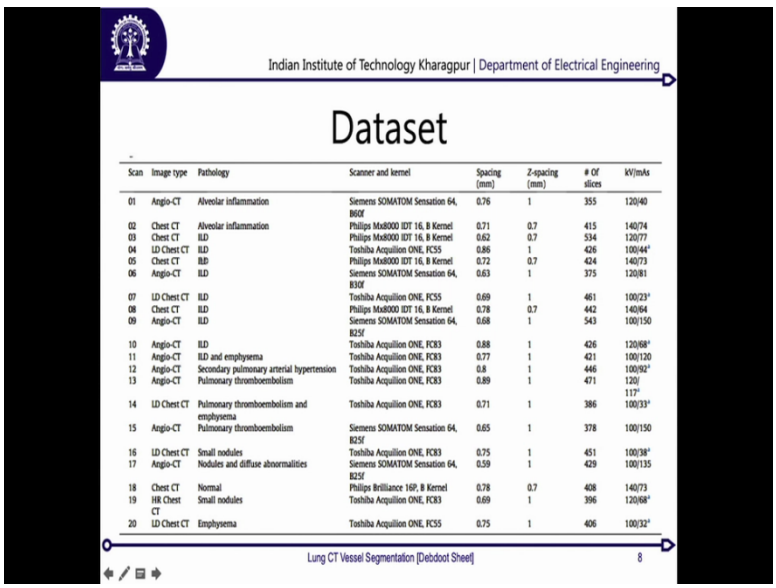

Scan	Image type	Pathology	Scanner and kernel	Spacing (mm)	Z-spacing (mm)	# Of slices	kV/mAs
01	Angio-CT	Alveolar inflammation	Siemens SOMATOM Sensation 64, B60f	0.76	1	355	120/40
02	Chest CT	Alveolar inflammation	Philips Mx8000 IDT 16, B Kernel	0.71	0.7	415	140/74
03	Chest CT	ILD	Philips Mx8000 IDT 16, B Kernel	0.62	0.7	534	120/77
04	LD Chest CT	ILD	Toshiba Acquilion ONE, FC55	0.86	1	426	100/44[a]
05	Chest CT	ILD	Philips Mx8000 IDT 16, B Kernel	0.72	0.7	424	140/73
06	Angio-CT	ILD	Siemens SOMATOM Sensation 64, B30f	0.63	1	375	120/81
07	LD Chest CT	ILD	Toshiba Acquilion ONE, FC55	0.69	1	461	100/23[a]
08	Chest CT	ILD	Philips Mx8000 IDT 16, B Kernel	0.78	0.7	442	140/64
09	Angio-CT	ILD	Siemens SOMATOM Sensation 64, B25f	0.68	1	543	100/150
10	Angio-CT	ILD	Toshiba Acquilion ONE, FC83	0.88	1	426	120/68[a]
11	Angio-CT	ILD and emphysema	Toshiba Acquilion ONE, FC83	0.77	1	421	100/120
12	Angio-CT	Secondary pulmonary arterial hypertension	Toshiba Acquilion ONE, FC83	0.8	1	446	100/92[a]
13	Angio-CT	Pulmonary thromboembolism	Toshiba Acquilion ONE, FC83	0.89	1	471	120/117[a]
14	LD Chest CT	Pulmonary thromboembolism and emphysema	Toshiba Acquilion ONE, FC83	0.71	1	386	100/33[a]
15	Angio-CT	Pulmonary thromboembolism	Siemens SOMATOM Sensation 64, B25f	0.65	1	378	100/150
16	LD Chest CT	Small nodules	Toshiba Acquilion ONE, FC83	0.75	1	451	100/38[a]
17	Angio-CT	Nodules and diffuse abnormalities	Siemens SOMATOM Sensation 64, B25f	0.59	1	429	100/135
18	Chest CT	Normal	Philips Brilliance 16P, B Kernel	0.78	0.7	408	140/73
19	HR Chest CT	Small nodules	Toshiba Acquilion ONE, FC83	0.69	1	396	120/68[a]
20	LD Chest CT	Emphysema	Toshiba Acquilion ONE, FC55	0.75	1	406	100/32[a]

And for medical image analysis software development this is one major issue which you will have to take care of. So these people had actually released out the dataset which was multicentric and on multiple devices as well as this was on multiple like imaging protocols and organic nature, so there were images from angiographic CT, there were images from a chest CT. So angiographic CT is where you put down a contrast agent within the blood vessels and then you take a CT over there which is also called as a CT angiogram.

And in the normal chest CT you do not put down an contrast agent you just raw, take down raw images on the CT from there. Then so out of all of this you also have a HR CT of the chest taken down and LD CT of the chest. Now, each of them were taken down for a different kind of a pathological scenario, so they were not from healthy people at all, so they were from different pathologies and that included angular inflammation to pulmonary thromboembolism and all of these multiple ones.

And if you look on this column you see that they are from different scanners, so they make and model of each of these different scanners is set. On top of that the spacing in millimeter and the z sampling, so spacing in millimeter is basically when you have a CT scanner over there, so your transducer elements are spaced at a specific distance, your receivers X-ray receivers over there, now that is the slice spacing between the elements sensing elements.

And then we have the Z spacing between so this is the difference between the slices coming down and this is what the z spacing is. Now this z spacing is also quite different so there are sometimes the z spacing is 1 millimeter, sometimes it is 0.7 millimeters. And then you also have different number of slices coming down as well as the total excitation energy of the CT tube and the current being consumed is also different.

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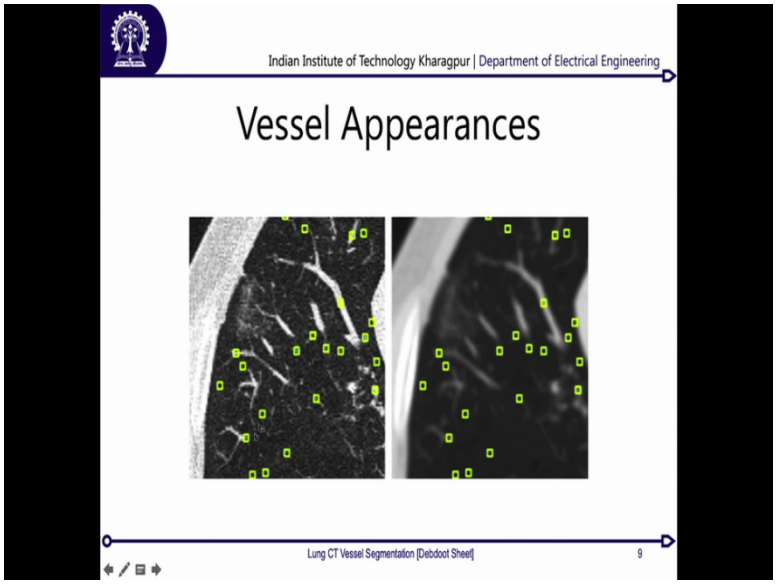

So obviously the energy of the X-rays which were emitted from the X-ray tube within the CT when taking this CT was also different. So you have all possible kinds of variations which can happen in this kind of an imaging environment captured in diversity in this particular dataset. So if we get into the vessels over here, so on the vessel appearance model you would see that all of these yellow spots over there they are basically all the points which have a vessel, but then if you look into one of the slices you will never be able to find down all the vessel because some vessels may be orthogonal to the plane of my imaging over here, the ones which are aligned along the plane of imaging say these ones are the ones which are visible on this particular plane. So that is a major challenge and the moment say, I do some sort of a blooding I lose all of them out.

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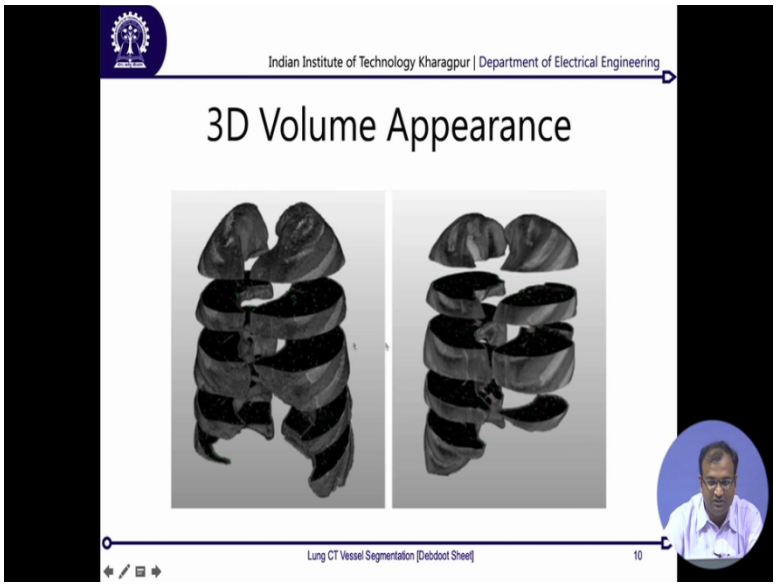

So people use something called as a 3D volume appearance model, so the images are not quite high resolution visible over here, you can definitely go down to the paper from where I have taken down which is linked at the end and that is a summary paper for the contest. And then you can also run down your 3D visualizations in order to see down the whole vessel map in a much better way, so we had done very early demonstration with (()) (21:57) where I was showing you how to open up dicom files and so it. So over here also you can use dicom files and then rub down your own slicer arguments within the dicom viewer over this, so that you can see a group of image slices coming down and you have a 3D visualization.

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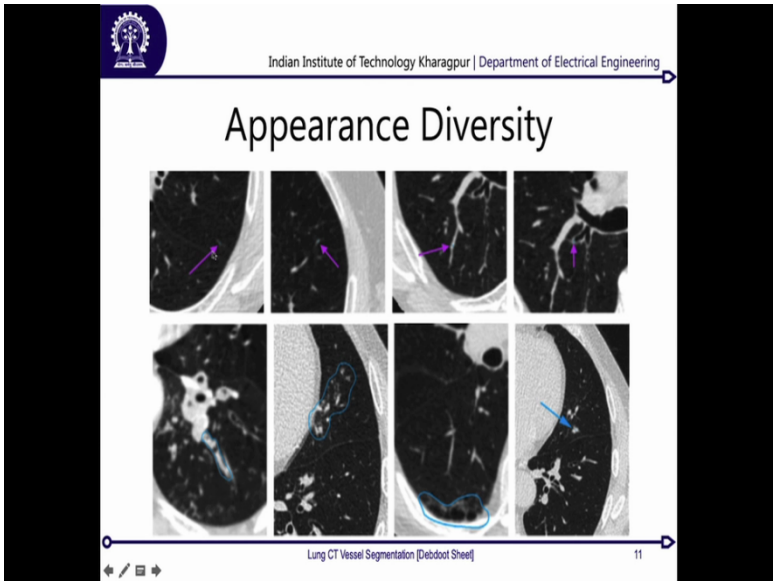

Now, the whole rational over there was that there is a lot of diversity in the appearance of these vessels. So if you look over here you would see this thin vessels appearing and most of them are some sort of obliquely aligned to the plane of imaging. So this actual plane along which I have taken down this images. So this is my whole body and I cut down this way so that becomes my actual plane on which it is done and that is the primary conformal plane of imaging for a CT because your gantry is rotating like this and the person is moving like this, so you would just be getting down actual scans over there. Now in some high resolutions versions you have these small ones very easily visible but then this one over here some of them are very low resolution and often this bundle of vessels which you see over here that would get mistaken for some sort of a mucinous deposit or other kind of an appearance abnormality.

Or sometimes they are like over here it is possibly not a vessel but then it has something in appearance which is similar to that. So these are all the challenges which you have been looking down on it 2D space instead of a whole 3D space from the vessel segmentation problem. So there were a lot of teams who had submitted so some of them had submitted before the challenge and some of them had submitted after the challenge had closed and they had taken all of them. So there so we just have alphabetic numberings over there and the details of the teams are I am not discussing much about them over there.

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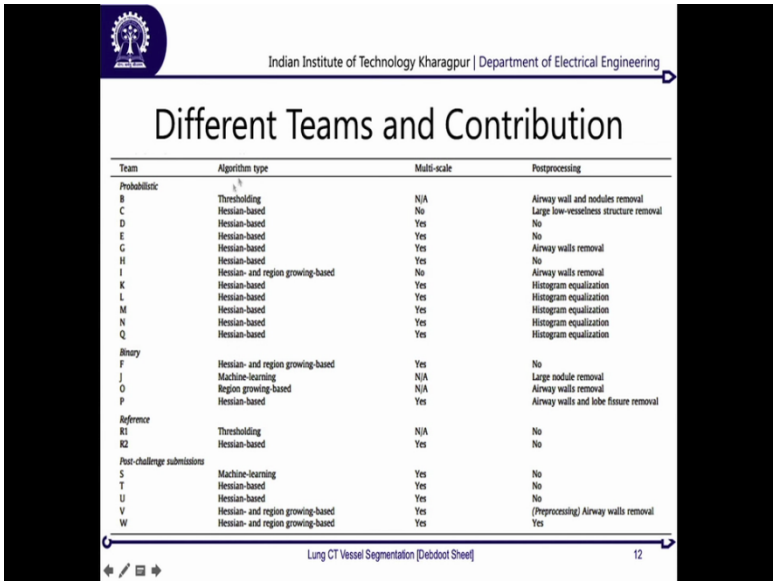

But what I wanted to predominantly say is that if you look into their approaches so you can broadly classify them into probabilistic approaches which one of them uses thresholding and most of them use the hessian based approach. So either they go down by Frangis native method of taking the eigenvalues corresponding to the eigenvectors of hessian decomposition or they use hessian decomposition and then on top of that use some other operators or learning engines in order to build on top of it.

So then there were approaches which were say binary and what this binary so all of them were giving a soft valued classification, so a probability of a voxel being associated with a vessel or not. There were other methods which did a hard classification either that voxel is a vessel or not. So over there were some approaches which were using hessian with a region growing approach, there were obviously machine learning based techniques which use support vector machines, then there were region growing and a pure hessian based techniques.

The references R1 and R2 are basically R1 is a thresholding based approach which is just based on a hounsfield unit you draw a hard threshold, if your hounsfield unit is between this value and this value, then that becomes a vessel otherwise not, so that is a thresholding approach. In the other one it is a hessian based approach which is a direct implementation of Frangis method which we had discussed earlier.

Then there were a few other ones which were submitted beyond the challenge, so there you not go on to win any prize or anything, but they were also included as part of this paper

publication and there also majority of them had a hessian based and region growing based approach. So this is a total summary contribution, you can read much more details about each of them because already we have done those linear algebra concepts and texture measures and learning systems in the earlier weeks about how to analyze images. So this is a consolidated summary of different approaches which people can use and there is no such thing as one model fits all or there is one superior model over there. So everything has its own pros and cons.

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And coming to that I have a visual comparison of these different kinds of methods which were performing, so each of these columns is from a different method, the first column is obviously a ground truth which was marked down by the human observer. If you see on the all of these red markings which you see over here are the pixels which are marked down by a human expert saying that this is actually a vessel. So they look in to the 3D space and the markings was in the 3D space, we just take down one of these 2D slices and then visualize the markings over here.

The second, third, fourth, and fifth rows over the third, fourth, fifth and sixth columns over here, these are the ones which correspond to output of different algorithms. Now if you look over there, obviously some of them are not that good, some of them are pretty efficient and close to what a ground truth is. But then there are some of them which are far away from that including like this just not detect over here and over here it is a curious case because it detects everything around this particular vessel as a vessel, but it does not say that this vessel is actually a vessel location.

So from this you have a very clear idea that it is obviously not a single shot go through problem, but then obviously starting with one of these techniques you can find out a much better way of doing it. So from there although segmentation results and everything are there in the paper and I am not revising it once again. The accuracies from this challenge are pretty impressive because you get down highest accuracy which is quite close to more than 90 percent as reported over here and some of them like most of them have a gross average performance which is similar although they use a different method which emphasizes on a different aspect.

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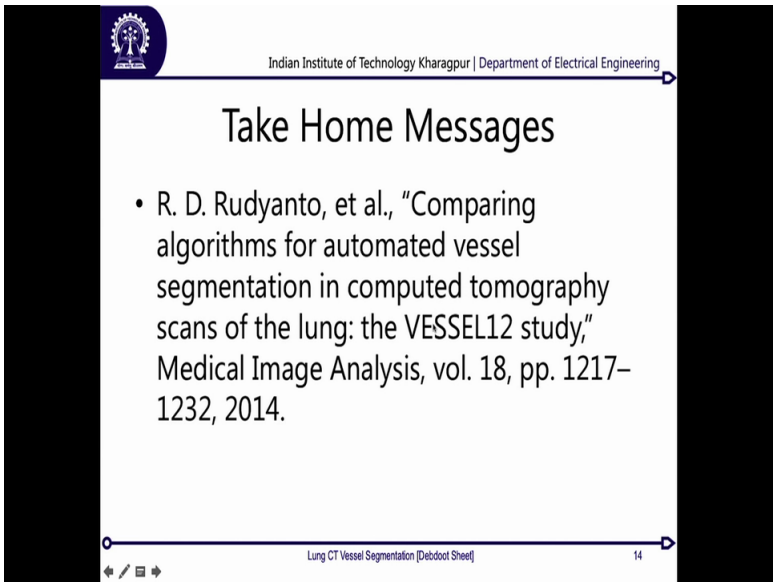

So obviously you can look into the specific aspects of the paper where they see as to the performance for thin arteries versus for thin vessel versus medium size vessel versus large size vessel and which method is strong for which of them, so just have a careful look through it. So with this as we come to the end, this is the main paper on which I am referencing to. So just go through this one which is the consolidated study for vessel 2012 and this was a (()) (27:44) publication from 2014. Now with that I come down to yet another interesting conclusive note about the problems which we solve on medical image analysis and one case scenario with computer tomography image analysis. So be tuned up for the upcoming ones on MR as well, so with that thank you.