Introduction to Biomedical Imaging Systems
Dr. Arun K. Thittai
Department of Applied Mechanics
Indian Institute of Technology, Madras

Lecture - 09
Blurring and Noise

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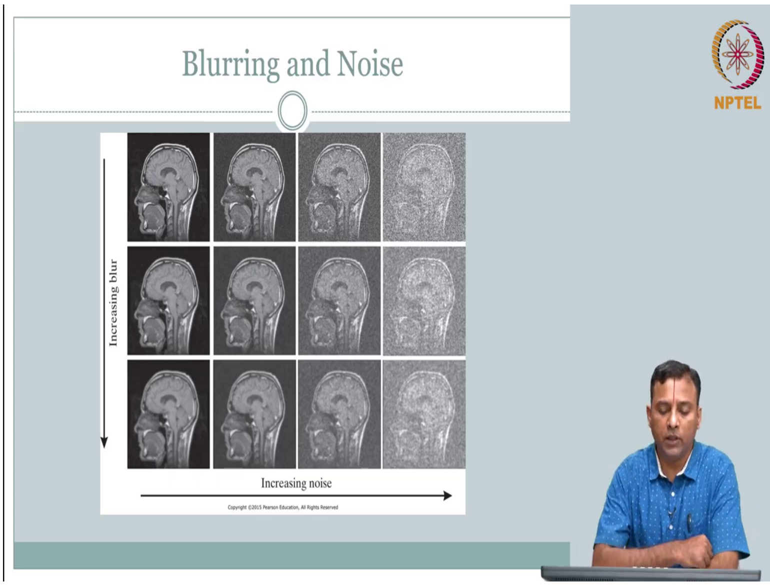

Ok. So, we talked about Blurring and Noise. All of these are aspects that are affecting our image quality right. So now, we need to proceed little bit further in understanding how to characterize this noise, saying that noise is something undesirable right. It is fluctuation around the ground truth.

So, you are estimating some signal and the fluctuation around that is a noise. So, beyond merely saying that noise is detrimental and it affects the image quality as viewed in this example here, we should go one step ahead and see if we can characterize the noise, capture the noise, understand using that captured model, is there a way that we can minimize the noise eventually right. So that is the goal here.

So, it is going to be a very brief overview. When we get into the individual modality right later on, that time we will again recall some of the basic overview that we did know and contextualize within the context of the respective modality. So, here it is going to be little broad-brush.

I would kind of warn you right. You should not look at, so this one what we are going to cover in the next few slides if you find it very unfamiliar the suggestion is please go get yourself familiarized with ok. Because these are something that are considered very basic that you almost like you would have encountered by now.

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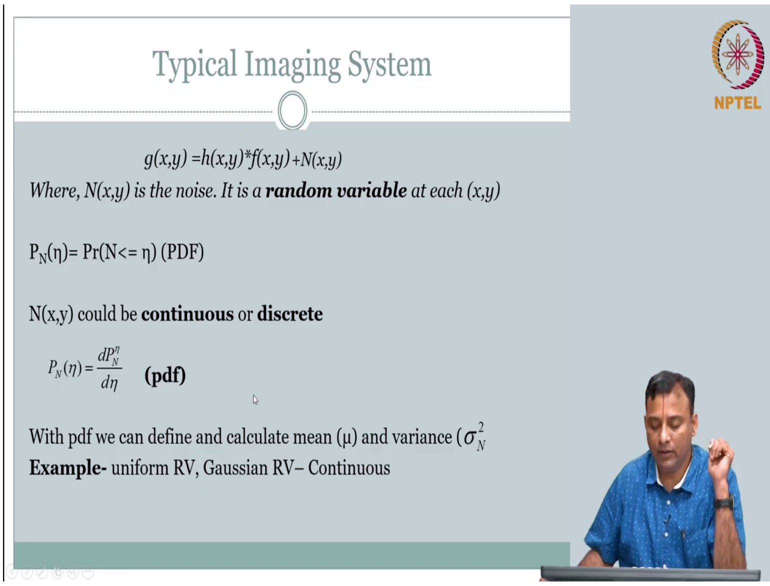

So, what we have done so far is, when we talked about imaging system we said g of x comma y is your output f of x comma y is your input right. So, underlying 3D ground truth distribution is your f of x y. The objective of medical imaging system which is characterized by h of x comma y is to capture the ground truth right from inside the body and present it as a output image g of x comma y.

So, if you recall the block diagram g of x comma y should be as close as possible to f of x comma y. This f of x comma y is the 3-D distribution of whatever parameter right, that the imaging system is going to exploit to see inside the body. So, this is fine, we have covered so much using just this model, but in reality the moment you are going to use a system to measure right then there is going to be noise.

And so more correctly this model should be updated with a term here that characterizes that stands for noise. Noise at x comma y since your image is going to be spatial right. Each location there is going to be an estimate of the ground truth right. Whatever is f of x comma y is the ground truth, g of x comma y that location is estimating what is supposed to be there at f of x comma y using the system h of x comma y.

So, there is a noise at each location, each measurement that you are doing. So, now we need to talk about little bit more about how do we understand characters, what are the common source of noise, how do we describe them right. So, good news is ok this model seems complete, that is I have in reality I know there is going to be some noise, so we have put a term here to account for it. But if you really look at it we say its a fluctuation around right.

You have an estimate the ground truth that you want to measure, when you measure that you are always going to have a fluctuation around the ground truth. That fluctuation is what is called as noise right. So, in some sense it is going to be random right. It is not going to be deter random means it is it cannot be determined you cannot say this is going to be the value 100 percent.

So, it is going to be random. So that means, you need to brush up. So, the idea is if it is random that means, we cannot do anything about it, so we will have to live with it, is that one approach or if it is random maybe we can understand certain thing, certain parameters about this randomness. So, I will we can capture this randomness and then use it to our advantage right.

So, the beauty of random is, although you cannot say with 100 percent certainty what the value is going to be, there are well different defined theories about randomness, quantifying this randomness, measuring some quantities to describe the randomness and therefore you can all these based on probabilities and therefore you can still make use of the knowledge to see how you can reduce the noise ok.

So, N of x comma y is the noise, it is a random variable. So, all of the random variable stochastics, random processes those courses that you would have taken, you should probably brush it ok. Random variable at each x comma y so that means you will recall probability distribution function, probability density function right.

So, you have probability distribution function capital PDF is nothing, but the probability of that N less than equal to the eta right, it is below a certain value. So, now N of x comma y could be continuous or discrete right. So, then you will have to recall ok, there is continuous random variable, maybe discrete random variable. So, you should start to recall some of the probability density functions right.

What is the relationship between distribution function and density function? So, please go review those, here we will quickly just say ok you have a relationship, so you can get probability density function from probability distribution functions, so they both are related.

And the moment we say probability distribution function of a random variable, you should recall some of the commonly used probability distribution function. You should know how to write mathematically common pdfs. What are the common pdfs that come to your mind by this time? There could be uniform distribution, there could be Gaussian right, that is something that you would have encountered which you will encounter even here, Gaussian right the normal distribution.

So, these are very essential. You need to go brush that up look at the you know formulation how it is described so that I leave it to you. But, why is this advantageous to have a pdf? So, I said it is random, but then you can capture the randomness right using certain attributes right. You have a probability distribution function. You can describe the distribution function using some statistics, right some attributes of that function.

For example, most commonly the expected values right. So, the mean and variance right. So, there could be several expected values right that could be associated with the distribution function. But something like a Gaussian for example is unique. If I know just the mean and variance I know the complete distribution function. I know the complete randomness right. So, there are several desirable characteristics that make Gaussian very relevant and very appropriate for several of the noise models. Of course, you will also encounter uniform random variable right.

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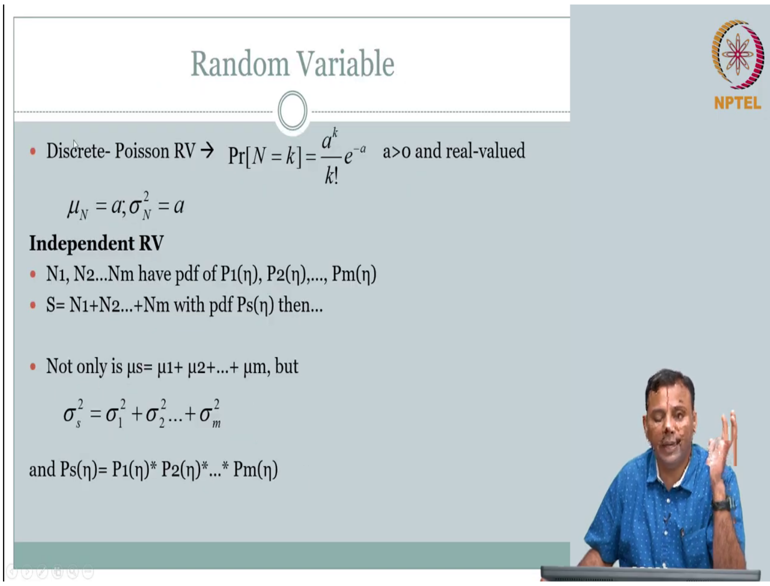

So, you need to brush up those two at the least. The other one that we will encounter is discrete random variables. Even discrete, one of the common ones that we will end up using is Poisson random variable, discrete Poisson random variable. What is the Poisson? So, here again when it is discrete probability distribution function, we saw for continuous probability mass function.

So, please go look up about discrete random variables. When you have discrete random variables, one of the interesting pdf is your Poisson; Poisson random variable. What is its distribution? The probability that the N takes a value k, discrete value k is given by this distribution right here a power k by k factorial exponential of minus a; a is just a nonzero a greater than 0 real value.

But what is interesting about this random variable right? Poisson's random variable is this guy; mu is mean right, sigma m square is your variance look at this. So, your mean and variance are the same quantity a. So that means, this is a distribution that can be described if I can capture the mean and variance and it turns out that mean and variance happens to be the same value which is the a here right. So, why is this important in our context?

Because, Gaussian I think you would have heard several times in different courses as well. Poisson not so much, why is this highlighted here? Because, one of the modalities that we are going to do right X-ray imaging or nuclear medicine gamma all of these are photons.

So, there is enough statistical analysis that has been done to say that the photon energy that is coming and hitting the detector right. The number of photons that are coming and hitting that can be modeled right. There is a fluctuation there and that turns out to fit a Poisson random variable and therefore this since we are going to cover X-ray based modality and nuclear medicine based modality, so the imaging system context because of the nature of the physics right.

The photons that are coming in, the number of photons that are coming and hitting the detector area that has been found to be modelled. The fluctuations, there has been found to be modelled with Poisson's random variables this will come in very handy ok. Of course, when you do that you will also encounter, when you do that as an review the materials you will encounter independent random variables right.

So, you can have different random variables not just one. You could have multiple random variables N 1, to Nm. Each one could have their own distribution. What is if interest is? Sum of all. So, you could have noise coming from different subsystems for example, different source.

We are not really bothered about that; we are interested in saying the end image quality is affected. Our objective is to reduce that noise, understand that noise, characterize that noise and try to reduce that noise. So, if you have multiple sources that are contributing multiple random variables, then we are still effectively looking at a combined effect ok.

Of course, while we are here, when you have multiple random variables right, independent random variables, what will be the sum of? So, you have a random variable which is sum of different random variables. What will be the distribution for S? Ok, go review why Gaussian is very powerful that is the clue I am giving.

So, if you have sum of multiple random variables; independent random variables then the distribution function of that random variable right, the sum of random variables tends to something ok. So, please go look that up. So, these are aspects which you probably know. I just want you to take that extra effort, go back to your textbook from previous semesters on say stochastics random processes and flip the page and you will quickly recognize some theorem that I am talking about ok.

So, if you have this, then your mean of the signal is sum of all and your sigma s square is sum of which is your variance is sum of all. So, this is very advantages of independent random variables. We can simply do this. If you have sum of independent random variables mean just adds up, your variance just adds up ok.

And then is your convolution operator if you recall ok. So, this is something that you need to brush up. And then another thing that you would have encountered is when we talk about noise ok. So, we have this random variable. We talk about capturing the mean and variance right. Then let us talk about some of the noise that you might have heard ok.

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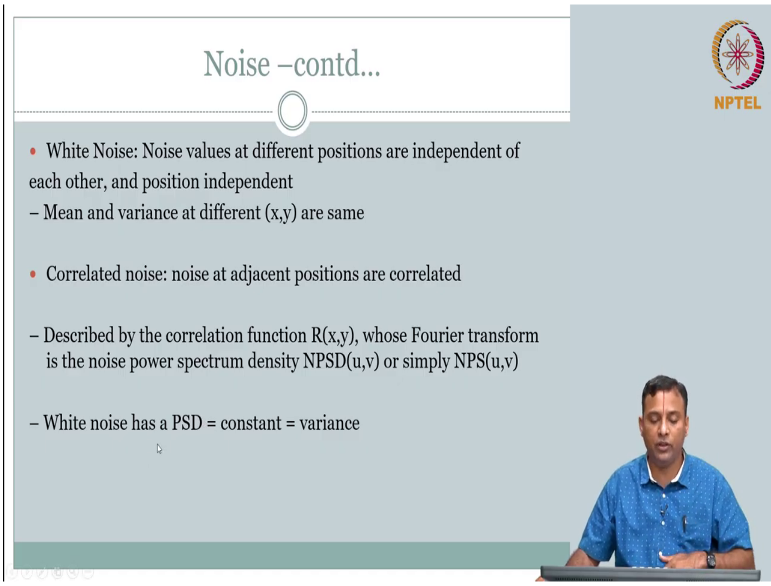

First thing is white noise. I am sure you would have heard this. What does it mean? It means that noise values at different positions. Two things, it is independent of each other. So, I have x comma y right that is different locations. So, what is there at one location does not depend on what is there in the other location. This is independent of the other location. Not only that, even with that the noise that is at one position or in another position is independent of position.

So, noise at a position is independent of that position and noise at two positions are also independent ok. So, if that is the case then we get what is called as white noise. So how do we write about write it in terms of whatever we have covered so far, how does the distribution function look right. So; that means, mean and variance. So, when we talk about noise values are independent of each other; that means, mean and variance at different locations are same and it is, it does not dependent on other location.

So, if you have white noise which are independent, then naturally there should be the other case where there could be some correlation. So that is called as correlated noise which effectively says, if it is not independent there is one location, there is another locations or noise at one location is somewhere related correlated to noise at another location. So that is what we mean by correlated noise. So, the noise at adjacent positions are correlated.

So, if you say something is correlated then you should be able to quantify the amount of correlation right. So, what do you do right? You will get into this correlation, describe a correlation function. The interesting aspect is correlation function is in spatial right. Different positions how they are correlated that is the spatial signal if you would like to call it that way or think about it that way. If there is a spatial then you have a counterpart in frequency domain.

So, you take the Fourier transform of correlation right that gives you what is called as noise power spectral density. So, if there is a correlated noise right if there is some correlation, so essentially you are correlating different positions in so I am using correlation function. That is in spatial domain, if you take the Fourier transform of that in frequency domain what you get is the power spectral density, but we call it noise power spectral density right or simply noise power spectrum u comma v, ok.

So, now what are we interested? We are interested in getting to what is white noise, what is correlated noise ok, have some functions we have introduced for correlation. So, how do I put them together? So, white noise has your power spectral density will be constant right. So that means, constant means in over the x entire u v right, everywhere it is the same value. So, irrespective of the frequency u comma v you have the same value of noise, that is what is white noise, ok.

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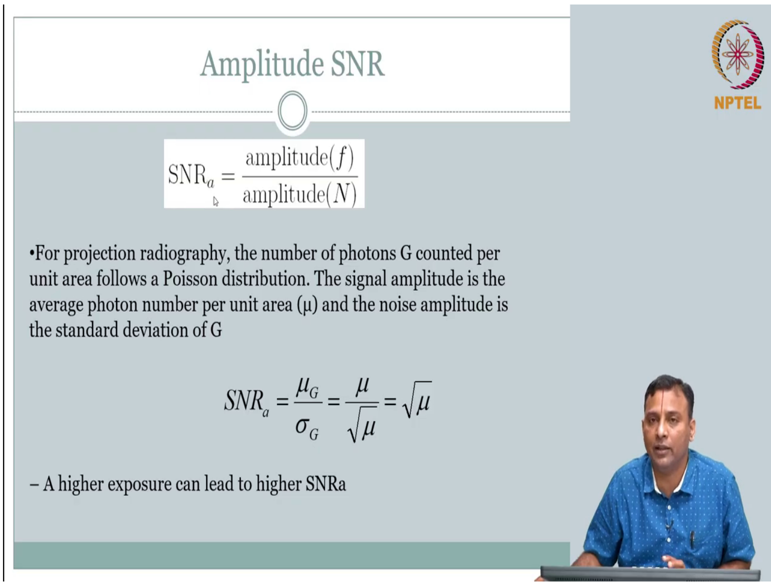

So now, I mean always the point is noise is something that we understand, characterize you know use all the simplifications for example, take white noise for example, right we say independent noise is independent and therefore we can use white noise simplification.

Why? Because, it is easier to say that all the frequency components are contributing the noise is coming from all the frequency components. That is what that white noise meant right. And almost always noise you do not talk it in talk about it in isolation. Because, our interest is not actually noise right. What is our interest? Our interest is signal.

The only problem is, while we are trying to go after the signal, while we are trying to estimate the signal, you are not able to get to the exact value because of some random fluctuations. So, the noise comes, I mean fortunately or unfortunately you are now not able to talk about signal in isolation, the ground truth in isolation.

You are ending up talking about noise in the context of signal. So therefore, what is more appropriate, what will be used most of the time when you talk about image quality is signal to noise ratio. Ideally you want only signal, no noise right. That is your ideal scenario.

But we already talked about there is going to be, because you are doing an estimate there is inherently going to be some fluctuation which will contribute to the noise. So, you are going to have signal to noise, that is more important to capture the quality. We already saw the effect of noise right in that sagittal image.

So, it is degrading the quality. When we say degrading quality, we saw that the contrast was going down, the resolution was going down. In fact, we talked if the resolution is poor, the contrast probably goes down. So, noise did the same effect right, you put noise there, the image quality was going down.

So, in some sense if you were to talk about image quality it is just not noise per se we would like to talk about the quality in terms of signal to noise ratio. Then the question is how do you define what is signal, how do you define what is noise, right? So, here for example, one way, one metric that is used is, because you are, see you have a quantity that you are going to measure.

So, I measure at that location. Now you are telling me if I make one measurement right at that location that is not ground truth, because there is a system there is a noise to it, and therefore the one measurement that you made is not the ground truth signal amplitude, right.

So, then what do I do? So, one way to look at it is ok, I can do signal to noise ratio based on amplitude of the function to amplitude of the noise. So, where do I get my noise? I get my noise because of fluctuation. So that means, at that location I will do like, so the signal itself is also random, but I want the ground truth signal, because that is my signal noise is corrupting it.

So, if you did random variables, if you did all the estimates right, what quantity did you come across which is the unbiased estimate that we can use for signal amplitude or if I have multiple measurements, mean right mean is the unbiased estimate. So, that what that means is? If you do mean, multiple right N times number of observations goes large you do this multiple times then your mean estimate actually gets to the actual ground truth right.

So, you could use amplitude, then what is your noise? Noise is fluctuation. What is fluctuation in the random variable? Variance, but numerator is just amplitude, here variance square, so I could use standard deviation. What is standard deviation? It is fluctuation around the mean which is what our definition of noise is.

So, one way of capturing signal to noise ratio is using the mean to standard deviation of the estimate. Why is this important? Let us take an example right. So, we will start with projection radiography you know when we start the modality, but for now without going to the details let us say in here what we will encounter is we are shooting X-rays right, X-ray photons through the body.

So, number of photons that are counted like I said, when we talked about Poisson distribution, number of photons G counted per unit area follows a Poisson distribution. So, what you are given is the characteristic of the signal is given ok. What I mean by a characteristic is? It is the number that is coming, you send number of photons, number of photons are coming through the body on the other side.

It turns out that the number of photons counted per unit area follows a distribution, a Poisson distribution. So, in this case what will be our signal amplitude? Signal amplitude is number of photons that came through the body at that location right. We are projecting, it is coming out your detector is capturing. So, number of photons that came whether it is attenuated more or less in the path that is the idea right.

So, you will get number of photons captured. So, the average number that is captured is your signal. So, what will be our noise amplitude? Noise amplitude is going to be the fluctuation around the mean, which is your standard deviation. So now, given this information can you calculate the signal to noise ratio for this. So, you will write out, I have mean mu noise is the standard deviation.

So, mu by sigma of, what is the random variable here? Random variable is G. So, mu suffix G by sigma suffix G is your signal to noise ratio. Can you simply see this any further? Do you have any other clue? Do you, can you simplify it any further? So, write down mu by sigma right. Is that the final form, can you use any other information? Quickly, that is why I said you should recognize. Do you know anything about the distribution? I know it is the Poisson distribution.

If it is poison distribution, what is the clue you have? I know the mean mu is equal to variance, both are same value right. What is standard deviation? Standard deviation is nothing but square root of my variance. So; that means I can have my mean and standard deviation are related right in this specific Poisson distribution. So, signal to noise ratio amplitude is mu G by sigma G, but I know mu G is for example, mu and sigma G is square root of mu.

Why? Because that is by Poisson distribution where your mean and variance are same. Standard deviation is square root of variance. So, what do you get? You get signal to noise ratio amplitude is square root of mu. Fantastic! Without going further detail you should already look at it and say if I want good signal to noise ratio or at least if I want to increase the signal to noise ratio. All I need to do is increase my mu.

What is mu? Is the number of photons per unit area; that means, increase the number of photons per unit area. What does that mean? What does it imply? I mean I need to send more X-ray photons through the body right. So, then you see the problem, mathematically we will say beautiful. I know how to increase SNR, but the problem in medical imaging system and biomedical engineering in you know at the bigger level is, we will have to always take a patient you know human body centric approaches.

Safety is an important aspect. In order to increase the signal to noise ratio, if I start sending more X-ray through the body, you will see that is not a good idea ok, because of the ionizing effects and so on and so forth which we will carefully define going forward ok.

But you see the context plain application of the concepts mathematics so far, but we cannot just be blind, especially in the biomedical, we cannot just be blinded by our physics and math or our background from one of the core areas and say I can do it. I think there should be an appreciation for the interaction of all this with the context of human body ok. That is the point that we will touch upon this very often ok.

So, higher exposure can lead to higher SNR. So, we will talk about what do we mean by exposure, what do we mean by ionization, all that we will talk about ok. So, now your, so is there any other way to do it ok? This is based on amplitude I am sure you would have heard. You can get signal to noise ratio in terms of the power, power in the signal to power in the noise right.

That also you can. So, its you have to look at the definition in the context, how people have defined not just jump based on the numerical value say this is better or the other. It is just that they could have defined signal to noise ratio in their context slightly differently.

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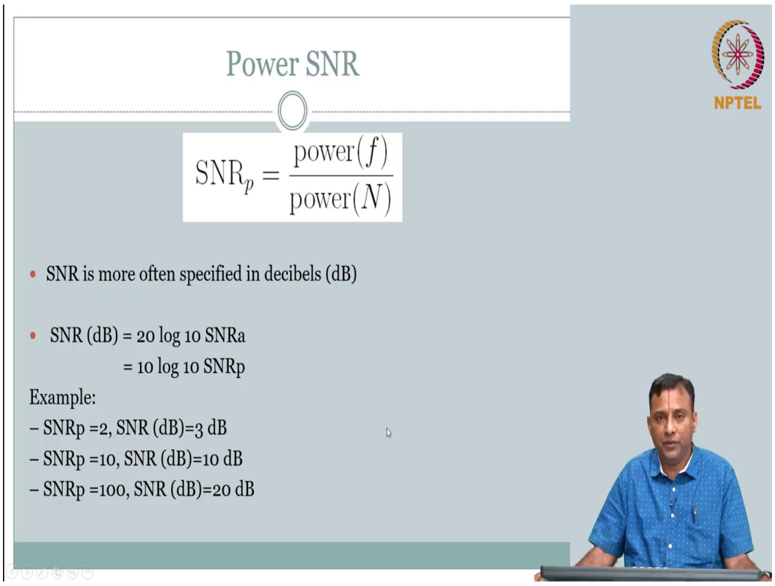

One another common way is power signal to noise ratio. So, when you do power signal to noise ratio typically you report it in decibels ok. And one of the most common mistakes that I find in this course and few other courses where I have this ratio of signal to noise ratio right. Sometimes you give the amplitude, but then the students use the dB formulation for power or vice versa.

Why? Because, signal to noise ratio in dB is straightforward, amplitude square is your right. So, you can think about a 10 log 10 SNR power or 20 log SNR a. So, how do you this factor, whether you are using 20 or 10 depends on whether the SNR is calculated as amplitude or as power ok. So, depending on that you will see, this is the ratio which is 2, 10 or 100, whereas SNR will be in dBs will be 3, 10 and 20 ok.

So, if I have SNR is 100 right, SNRp is 100 then log 10 100 log 10, 100 is 10 square right. So, 2 comes out, so that is your 20. So, that is your 20 dB clear. So, this is something that you need to get comfortable with. So, much so for signal to noise ratio power and amplitude signal to noise ratio.

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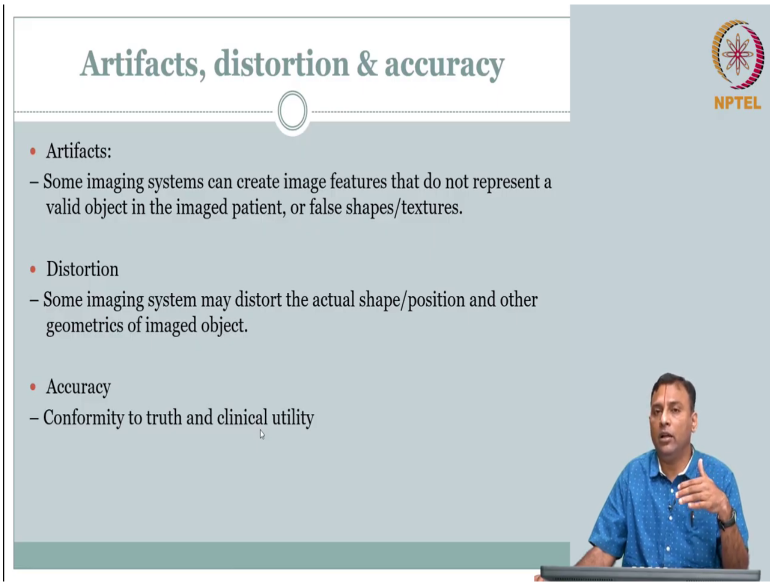

Let us move on a bit and talk about the other source of other factors that affect the image quality. Artifacts, distortion, accuracy. Artifacts; what are artifacts? That is also noise is what because it distracts the signal right. That is, but then it is not quite so. Artifacts are something, see whatever we carefully define noise we talked about noise in terms of the randomness right.

So, each time you make a measurement you are not going to get the exact value because of fluctuation which is due to noise. Whereas artifacts are nothing but, you see something that is actually not there, you may some imaging systems can create image features, that do not represent a valid object or false shape or textures. That means, in my f of x comma y, I do not have something, whereas in g of x comma y I see presence of a feature ok.

If there is a presence of a feature or I see a circular shape when I know at that location there should not be a circular shape, there should be a triangular shape for example right in that cross-section view. So; that means, you have something that you are seeing in the image which is because of the imaging system that gives you an impression of an object which is either not there or the other features that are not corresponding to the ground truth.

That is your artifact. That means, each time you do it you will see the same effect right. So, it is reproducible in some sense ok. So that is artifact. We will look at few example artifacts. So, that you can get a feel for it. Distortion; distortion again is challenging one distort means; that there is a truth, there is a change, there is a difference from the truth right distorted from the truth.

So, it is the same context distortion means some imaging system may distort the actual shape poses this is mostly geometric effect ok and other geometries of the imaged object. So that is distortion. When we talk about accuracy, there are two types of accuracy; one is your conformity to truth right, I am doing some measurements, how close is the measurement to the actual ground truth, that is one kind of so which we call as conformity to the truth.

The other accuracy is I am using this imaging modality and I am trying to use the image to do some diagnosis right. The doctor saying based on this you have, you know you have a tumor that is stage two or you have to go for a surgery. So, he is making some assessment based on the image. So, the other accuracy has to do with clinical utility.

How many times the decisions based on this image features from this image is how does, how accurate is it to the ground truth clinical condition ok. So, that is clinical utility. So, we will kind of quickly go through all of these in the next few, next 10 15 minutes or so ok.

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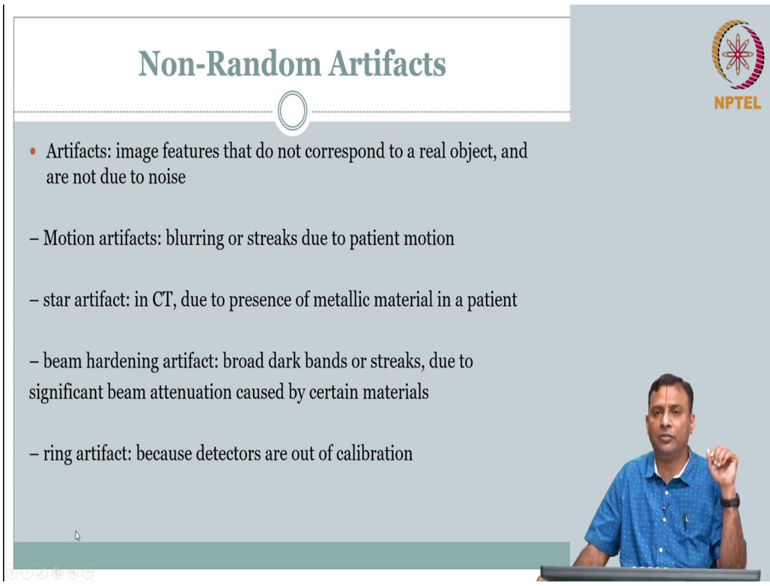

First is artifacts: like I said, non random as you can reproduce this, because I know how I can obtain that. So, artifact most commonly features that do not correspond to real object. This is the key, and not due to noise, because noise is random. If it is due to noise then it this will also become random. So, this is not random. I can in fact, create artifact because I know where it is coming from ok.

So, when we talk about some of the common artifacts that you encounter, some of which actually you might recognize the moment I put it right. Say if you take, if you take the recording system that is happening right your camera, video camera right, say let us take as you are taking a picture, let us not go into video, let us take a picture. When you do a picture right and your objective is to measure the width of my finger or width of my hand, whatever right, this is the objective.

You take an image you want to measure the width of my hand; I have a ground truth measurement that is there, but you are using the image to measure that. If it is noise then each time you take 10 photos of mine in this pose and each one if you are measuring the number of pixels that are there using some thresholding algorithm. Then each time you mean may or may not get the same value. There will be one pixel offset here and there are two pixel offsets every time that you make, that is noise. But artifact, if I have it here and you are going to measure it based on the image that you see of this.

Can you think of scenarios that you when, if you make a measurement based on the photo that you know is probably not the actual measurement that at least from your experience we can tell this is this happened and therefore, this is an artifact, so I will not trust the measurement right.

Easiest thing is, when you are trying to take a photo, I slightly move right motion. If I do motion what will happen? Blurring; that means, instead of the this size, while taking the photo if I move then it will be blurred and therefore, the width will become larger. So, you can tell from the image the sharpness went down and probably you moved. So, you have all these auto correct right motion deep blurring algorithms in a camera, but that is an artifact.

So, each time I can tell ok, if you are going to move at certain velocity I can actually create the same image again and again right. So that is your motion artifact is something that you are very familiar with or you would have encountered. So, blurring or streaks due to patient motion.

Another common one that we encounter especially, most of you would not have experienced it, some may if you have fractured a bone for example, or you have some metallic objects went in they did CT or if you have seen some you know movies where the bullet is fired and the patient is taken to the you know room to take a X-ray right or CT or somebody swallows, you see that this is the foreign object metal right not your soft tissue.

So, something when you take that you will end up noticing because of the huge difference in the material property, you will get what is called as star artifact. Especially, in CT this is very common, because you are doing reconstruction. So, we will talk about that and that is because of presence of metallic material in patients ok.

So in some sense, you artifacts most of it, if you encounter, if you can characterize that if you understand that you can try to minimize it. You can reproduce it therefore, right. And then something like beam hardening. So, this is little non intuitive right now. We will talk about this when we get to the physics, but essentially this happens because you see a sudden you know in the anatomy, you know the anatomy right.

The doctor knows the anatomy. Suddenly he feels that there is a broad dark bands or streaks that are not really supposed to be there for that anatomy you have seen it day in and day out. For normal patients that should not be a range of values that he sees there. But sometimes what happens is due to this beam hardening, artifact you start to see that and that is caused by sudden attenuation by certain materials right.

So, we will talk about that when we get in details about the physics of interaction of X-rays with material. Ring artifact; this is another nice one that spotted out ring artifact is when a detector is out of calibration. So, you have a detector array for example, and one of them goes bad, then you will see a characteristic pattern in the image which will be of the which will be resembling a ring. So, this is the common artifact that can that is fairly recognizable.

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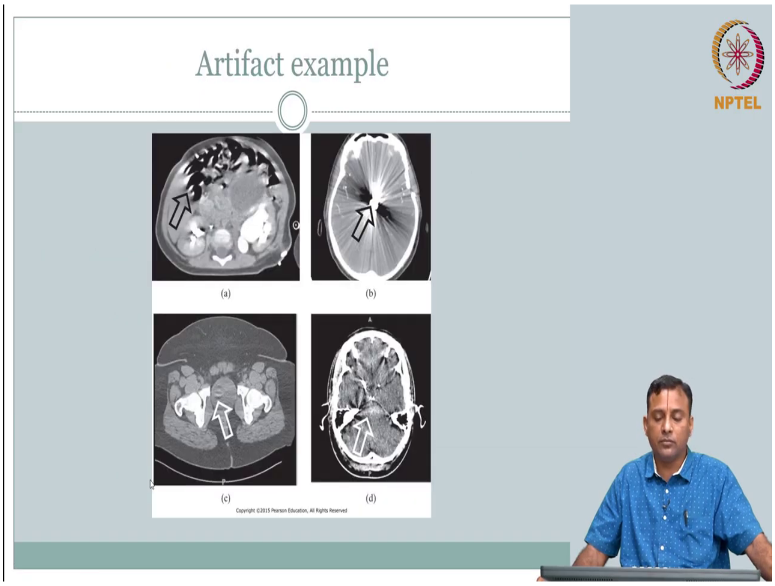

So, let us, if you think ok I think I follow all of this then let us take a quiz right. So, how does it look? So, let us get the easy ones out, easy one would be? There is a ring here, I see something, right it looks like a ring. So, it is a ring artifact which is due to detector miss calibration or element in the detector that is gone whatever.

And when you stand back and look at this you see like a star right, not really the star that you do, but you really you get the streaks here. It is like glow in a twinkling star. So, you see this is what they mean by star pattern we can actually make a very nice star that you think about right when you draw that we can do in your. In fact, you can do yourself when we do reconstruction we can see where it comes from.

So, this is star artifact or ok. So, if there is a strong object and you if that is the case then there is streaks because of the sudden change in the property. Now, these two are little. In fact, this is the most difficult one. This, if you knew the anatomy right, then you will you can guess you see some streams right it is. So, this is because of motion, it is moving, so motion artifact ok. This is what is the beam hardening.

This is a little difficult one or non intuitive at this point of time. This is very subtle to us, but for somebody who has been trained to look at these images day in and day out, they will tell this I suspect from my experience, I know this is not really the material property there, it is artifact due to beam hardening ok. So, this we will pay a little more attention when we get to the portion of beam interaction with material, ok good.

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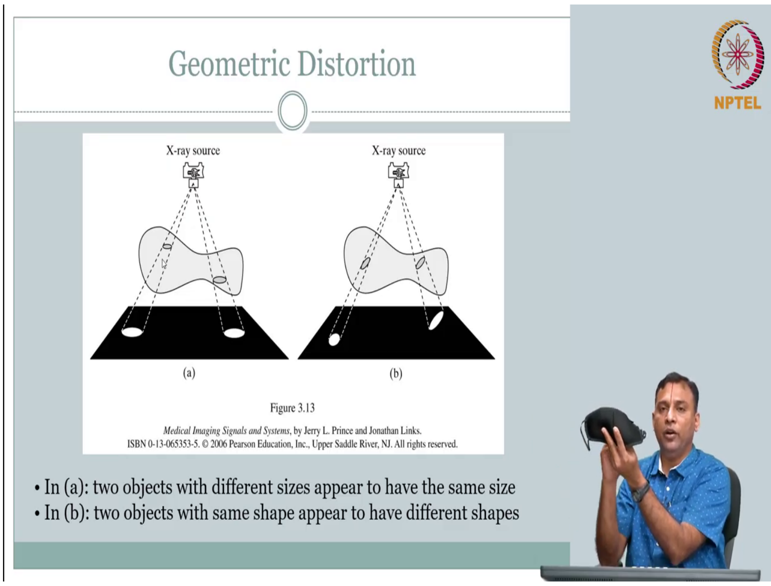

So, that is for artifact examples. Let us move on to the two other important ones, which is geometric distortion. So, geometric distortion means just recall its very pertinent. Just to give you a intuition before I spoil. So, let us use this camera system to our advantage it is just to give you the big picture idea.

So, the objective is, you need to measure the length of my fingers or width of my palm right or width of my forearm, that is the objective. So, you are taking this medical image right, you are going to do that. So, if I take the image now and give you, so I will give you only the image of the hand right.

You crop me out, you are taking the image of my hand and you want measurement of my width of my fingers or width of my palm right. I give you this image. I give you this image. I give you this image. What will be the measurement of my hand?

Wow, depending on where my hand is how much distance my hand is from the camera right, unless I have a correction factor calibration, unless I have that the number of pixels that my hand will occupy, my palm will occupy, my fingers will occupy, will be different when I close to the camera or far away from the camera. So, if you are going to measure and say so many pixels correspond to these many millimeters or these many centimeters, so my hand is my finger is 5 centimeters.

If you say the width is 5 centimeters because I am close to the camera, when you will say his hand is now 2 and half centimeters, but my hand is not changing right. It is only the position that is changing. This is very vivid. I mean you might look at this and say look this is not that of a problem. The problem is this is outside that you are doing.

What you want to use the medical imaging system is to see inside the body, actually I do not know where the right, I do not know if my lung nodule is the front of the chest or back of the chest, I just go for a chest X-ray.

The chest X-ray is going to put everything on the plane of paper. It is not going to tell me whether it is in the front of my chest or back of my chest, so right there is a distance. So, you cannot I mean so it is not that straightforward. I can calibrate for the outside, but what about inside?

I actually do not know how much they are separated, if I know I can compensate, the whole idea is I do not know, that is why I am going for medical imaging to non invasively see what is there inside. So, it is a very tricky business. So, you could have very complicated scenarios which are very significant, which affect to the outcomes in a significant way.

So, for example, here are the two scenarios, very simplified scenario. So, say this is the object and you are going for a X-ray imaging right, X-ray projection. So, if you have this you look at this the size of the object is different. Luckily here the shape are taken to be same. We can complicate that also in reality, you know you cannot force any shape right.

So, this is different size and located at different depths in the body, but if I take a image of this as a projection. I will get the same shape and same size. Clearly, this is not correct right. My actual object is only small here, now that is appeared to be big here in. These two were different are different, but my image of them, the projected image of them appears same ok.

So, you can make your best efforts to make sure that the object is kept from certain distance and your detector is kept at a certain distance, all that you can manipulate. But whether this say for example, if this is a tumor inside the body whether the tumor is here or tumor is there that you do not have control, I mean that is the unknown that is why you want the image and see if there is something.

So, if you are going to just have everything else and then make a measurement and give a protocol give a this is greater than 2 centimeter, so you need to go for surgery tomorrow it will become a tricky business. So, it is a challenging aspect. So, this is one way, the other is you look at this they are supposed to be of the same size and shape, slightly offset, but then they are projected differently. So, one becomes circular, the other becomes elongated ellipse. Both the scenarios are troublesome.

So, what do we do? This we can do the best we can calibrate it right, understand where our equations are coming, can we compensate for that? How do we do the instrumentation? How all what are the protocols that we can take right? To minimize this error, this distortion is all something that we should pay attention to however, it also has to do with the experience of the person who is doing it ok.

So, here we had two different scenarios these are very, in fact just for demonstration purpose these are actually simplified case. Life is more complicated. You can have different shapes; nothing is I mean if its perfectly spherical no issues. Whichever angle you are going to see its going to be appearing same right.

If for example, if you are doing the chest X-ray if I have a sphere whichever direction where you are doing you know front or back you are going to get only a circular cross section if it is a sphere. But reality, you may have wired shape right. So, for example, like here, how do I know if the hand I am showing, but for example, if I cover the hand right, I cover the hand right, difficulty of optical imaging, you cannot see inside the black, everything is getting out from there.

So, the idea is, who says my hand is like this, if it is like this it will give a different width, if it is like this it will give a different width, if I have this in front right, so I do not know which direction it is right, that is the problem, it is inside. So, which projection I will see I do not know. So, that is the challenge. So, I can distract do the correction for everything else, but still the you know the distortion is going to be a challenge ok.

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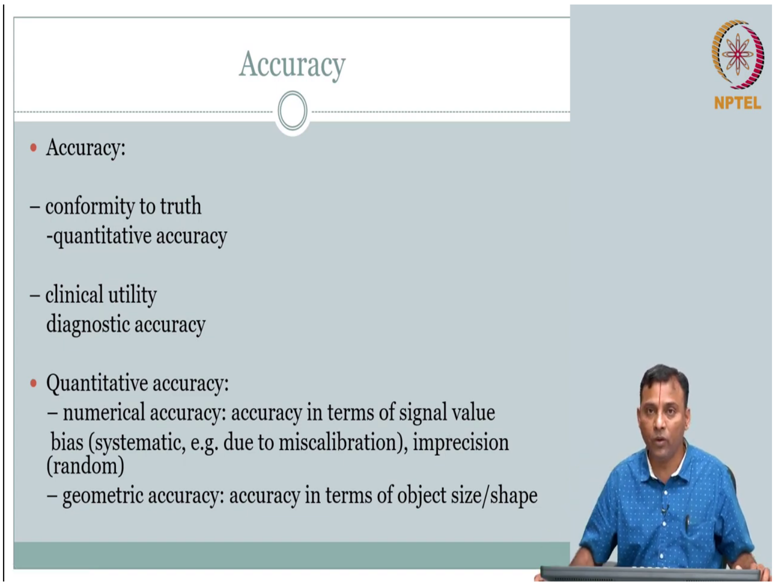

So, last but not least, in fact, the most important one is accuracy. In fact, an accuracy like I said, conformity to truth is one aspect. The other is clinical utility. What do we mean by conformity truth? It is what we have this quantitative accuracy. Recall your say for example, measurements and error if you had a course in measurements right or even stochastics, we cover that.

So, essentially you would have heard about this right. So, you have your quantitative accuracy is based on measurements right, the bias, precision all that you would have heard. Clinical utility means diagnostic accuracy. When you go for a diagnosis right you do some measurements of some parameters, clinical parameters and based on that parameter you say whether this is normal abnormal and so on and so forth. So that is your diagnostic accuracy.

So, conformity to truth or quantitative accuracy you know it has to do with the measurement side of it. So, it is a numerical accuracy in terms of signal bias ok. So, you could have systemic. So, if there is a miss calibration whatever is supposed to be 2 millimeter, I am just saying some number. 2 units is say millimeter.

So, I am measuring a tumor, size of a tumor in an image and it turns out the actual ground truth is 5-millimeter tumor, but because of miss calibration, when you take the image and you measure it comes out to be 1 centimeter right. So, then that means, it is miss calibrated that is the systemic bias. So, if I know that then I can immediately correct for it and say if it is 1 centimeter; that means I have to subtract half a centimeter because there is a bias, systemic bias so the actual size is only.

So, that is not a problem ok, that is your systemic bias. But then the problem is noise, it is not precise ok. So, that is your random part of it. So that is your quantitative accuracy. Likewise, your geometric accuracy, right now we saw right distortions. So, geometric accuracy is accuracy in terms of. So, I have a tumor, I want to measure the size? How accurate am I?

I think it is a spherical shape or is it elliptical or is it something in between. Do I make correct? Am I accurate in saying that is the circular one or elliptical with some b by a, I am measuring it. So, how accurately am I capturing the geometry? So, this is all based on the measurements ok.

So that is something that you will be involved because as a systems engineer, you will do that. But these are ok because this will be, you have control over everything you can have a calibrated phantom. Remember, we talked about this resolution bar phantom. Like you can have a calibrated phantom, every dimensions is known right.

And then you use the system and you characterize it. So, you can report all these quantitative accuracy, geometry all these you can correct for and do it. The challenge is, when you put it to a patient each patient is different. In fact, each patient is different; the same patient is changing with the time right. So, to that extent that is also different, so the challenges happen in clinical utility, ok.

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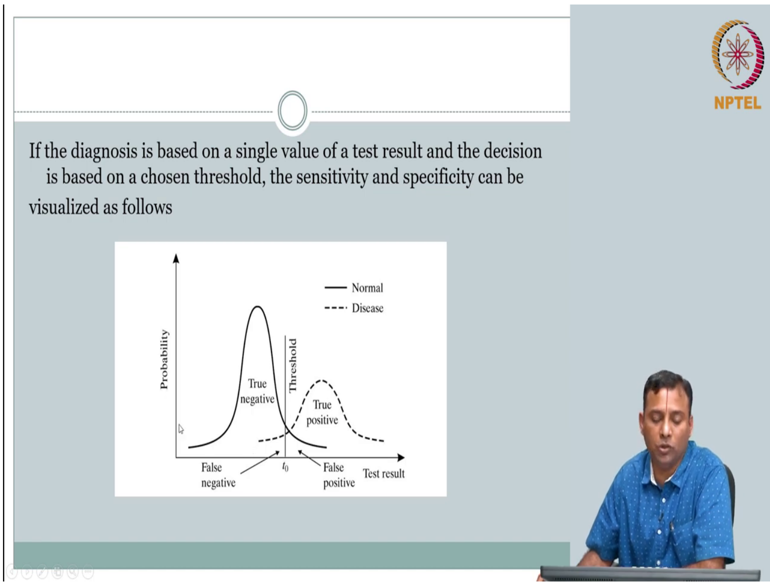

So, this is fine quantitative accuracy is more from engineering perspective that you can handle this. The more significant one is your diagnostics, diagnostic accuracy. Why? Because, that is having a lot of impact. So, I make some measurements from the image for example, and I say the size of your say kidney right, or size of your liver is supposed to be so many or volume of your liver is supposed to be so much.

But now I, a patient comes and you do the measurement, you do the image and from the image you are measuring it and you get some x value right. So, normal value is some N cc you measure it and you get x cc. So, now you have to make is this x normal, are you normal, do you have a normal liver size or it is bloated or shrunk you have to make that call.

So, you measure this parameter right, you measure the size for example, here and you have to make a diagnostic call. So, if you say you have a problem you know the size is larger than the normal and if you are able to get the ground truth value then you know whether the diagnostics is good or bad right.

Diagnostic how accurate is it to the ground truth. So, you do this parameter measurements from the image. So, which we call as test result and you have to make a decision. So, how based on that if you are making a decision, how good is that decision. That is usually used right, the terms like sensitivity, specificity, will be used to capture that ok.

So, example, here for a particular test result is here, it is always a probability only. Ideally, you want to be 100 percent certain ok. So ideally you want to be normal, this is a distribution of that parameter whatever. So, I said example is say size of the liver right liver volume.

So, for normal this is how the distribution is, but when there is a disease then you have a different distribution. Distribution is same, but then it has a offset. So that means, in this case if this is the size then size is increased size, but then the challenge always is, there are going to be people who are otherwise normal who could still have a small percentage of them could still have a larger size and there could be some people who are diseased right who will who may still have smaller size.

So, you are going to this is always a probability. So, you do this measurement, based on the measurement you have to say whether the person is normal or diseased. So, you have this distribution, you make a call if it is above a threshold, you say it is diseased, below a threshold you say it is normal, but then by doing that what you realize is, there are going to be some people who are diseased who you will send home saying that you are normal.

And there are going to be some people who are normal who you will send for further follow up because your threshold, it is greater than your threshold. So, you are going to diagnose them as having likely would have disease right. So, you can look at the so, then there is one population, where? They are actually normal and you have asked them to go home normal and there are people who are diseased, who have asked correctly to follow up.

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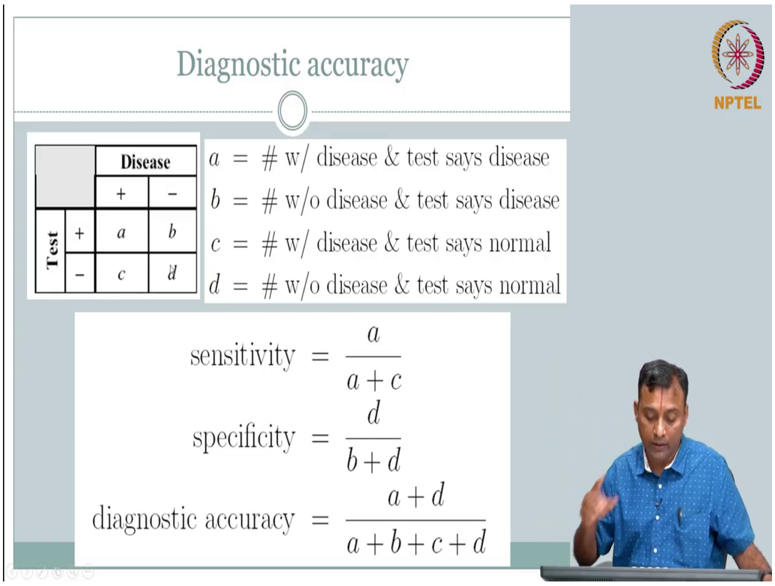

So, you have four instances right, you have four instances. So, you have disease is positive, your test is also positive. Your disease is negative, there is no disease your test is also saying there is no disease. But the troublesome is, there is disease and your test says there is no disease or there is no disease and your test says you have disease right.

In other courses when you have done this you would have heard people you know the confusion matrix ok. So, this is so; that means, from here you can get different values, one specifying right a b c d are the values here. So, you can have all the different cases with disease test what. So different combinations, for different combinations.

So, typically you are interested in sensitivity which is the fraction of right a, what is a? Disease is there and the test is also catching it and a plus c is the total number of people who have disease right. So, your sensitivity is how many times the test catches the disease amongst the total number of disease population right, that is sensitivity. If it is 100 percent sensitive means, all a plus c right 100 percent sensitive means I will not have anybody.

So, I will have one. So, all people who are having disease are captured. Specificity has to do with how specific you are, d is what disease is not there and your test is also saying it is not there. So, how specific if you say you do not have a disease and you ask them to go home how specific is it right. So, d by b plus d. So, b plus d tells about the population that are not having disease right.

Amongst the population that are not having disease, how many are you sending home based on the test also saying there is no disease right. Ideally, what is the case? You want to be 100 percent specific meaning, everybody who does not have a disease I want them to go home; that means, I will have the d, I would not, I should not have any b, b is there is no disease, but my test says you have disease.

So, I should not have any b. So, it will be b by d will be 1 right. So, in reality; obviously, your sensitivity and specificity are going to be less than 1. So, instead of doing it like that one metric that combines both is your diagnostic accuracy. Diagnostic accuracy is essentially saying, it is the sum total right.

How many times I correctly pick people with disease as disease and how many times when I say they do not have disease, they do not have disease. Both sensitivity and specificity combined together, both are decisions. When I say there is a disease that is the decision. When I say there is no disease that is also a decision. Both are correct decisions. Number of times how accurate am I in making the decision that is captured in diagnostic accuracy right.

So, it is a plus d; a plus d, both positive, positive, negative, negative. So, I do the correct diagnosis, a plus d is my correct diagnosis. Correct diagnosis out of the total decisions, total number that captures your accuracy. So, I think this is the good time to stop. What we will do going forward is start with the first modality of X-ray based projection radiography.

Thank you.