Biomedical Signal Processing
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Lecture - 40
Modelling of Biomedical Systems

So, now we will start a new session and a new chapter that is on Modelling of the Biomedical Signal.

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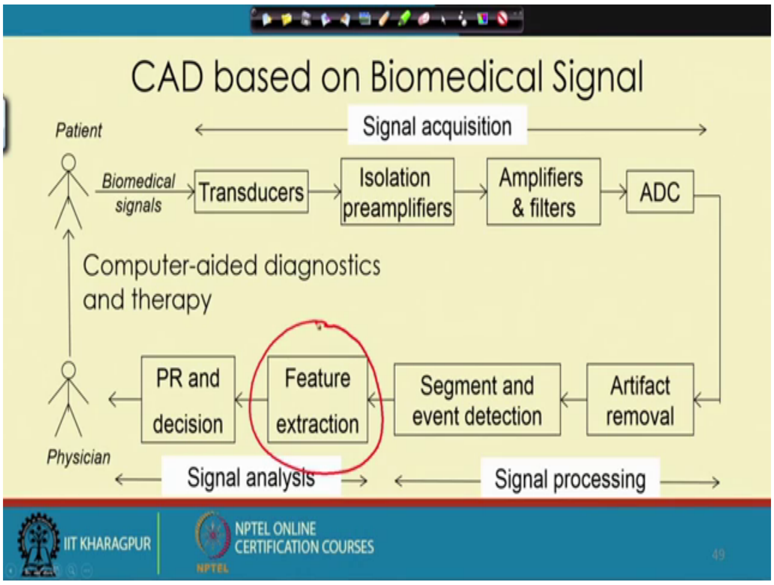

Now, if you look at our whole diagram; that the overall the goal was to find out that our biomedical signal from there that we have it has gone through number of stages like amplification filtering A to D conversion removal of artifact segment segmentation and the event detection.

Then after that we have come to the stage of the feature extraction; the previous actually the topic power spectral density estimation or periodogram, as well as our the present topic that is modelling of the biomedical signal both is concentrating on these part. Now before we go further let us get some idea about that the modelling.

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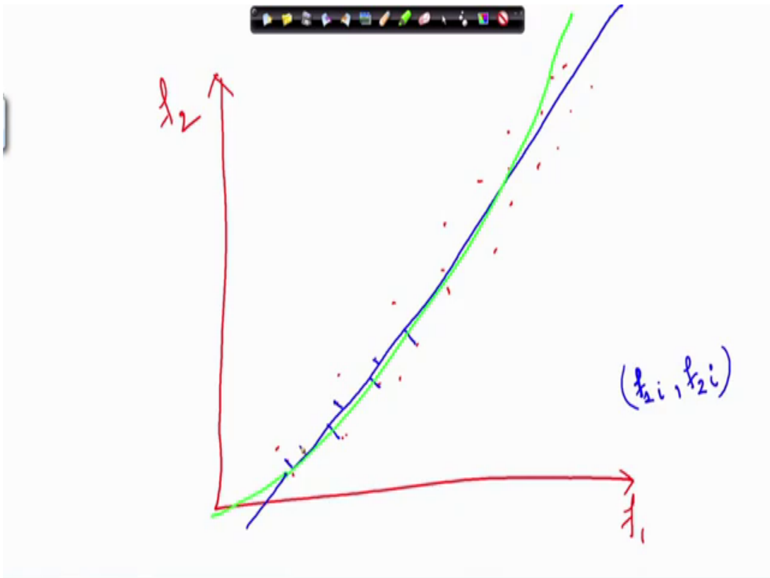

Let us take say couple of points in a 2D plane say we have x and y axis or if you want to take them as feature let us take feature 1 and feature 2. Now, we get some points we can add some more here and there as many as you want. Now, we can keep actually the information about all; instead of that if we fitted say straight line on them say we take a base fit line passing through these points; how that can help? If we are looking at keeping all this information instead of taking two pairs of values that is say f 1 say ith point i; f 2 i these kind of pairs we may just keep actually that how much is the error is there for each of these points ok.

So, that if you just take them errors; so, that can give us those values. So, it can be give us a compact actually representation of the data or data compression we can get. More than that what it can do actually that is very amazing when you think of that there is a huge amount of data, it is difficult to get the trend if you know that the variation should be linear then by fitting these straight line, we can get actually much closer to our system.

But when you have such number of data points and what can happen you may find that that instead of taking a straight line say if I fit a parabola it has a better fit ok. In fact, we know that more the higher the order that the error for that polynomial will be lower ok, but beyond the range what we will find for the parabola and for the straight line the 2; they would differ much with each other ok.

So, we would get actually two different answer in two different case; now this is where the beauty as well as the danger of the modelling lies. If you have enough information about the system if you know the nature of the model and if you select that model you can have actually a much better answer.

For example if you think that all these data they are coming out of a linear distribution f 1 and f 2 they should move in a straight line, they should have a linear relationship and whatever the variation is happening that is because of the error by fitting that straight line the amount of error suppression will have you cannot get that with all the other means what we have studied ok.

But if by mistake we take a straight line whereas, the real nature was parabolic; then at some range these two things you will vary a lot and this model would be a misfit at certain situation. So, parametric modelling we will see that it is a very powerful idea it can give us compression, it can give us very good estimate of the model or reflect that what is going inside if we think of that the removal of the noise to get that what is the real process we can do with the system modelling or parametric modelling or by signal.

So, all these things we can do very well, but that there is a crucial assumption before that that we know enough about that module and we have selected the right model; if that assumption goes wrong; however, the result could be catastrophic. So, we need to take care of that we need to make sure that there is no mistake in that and then we can really gain from modelling of the signal.

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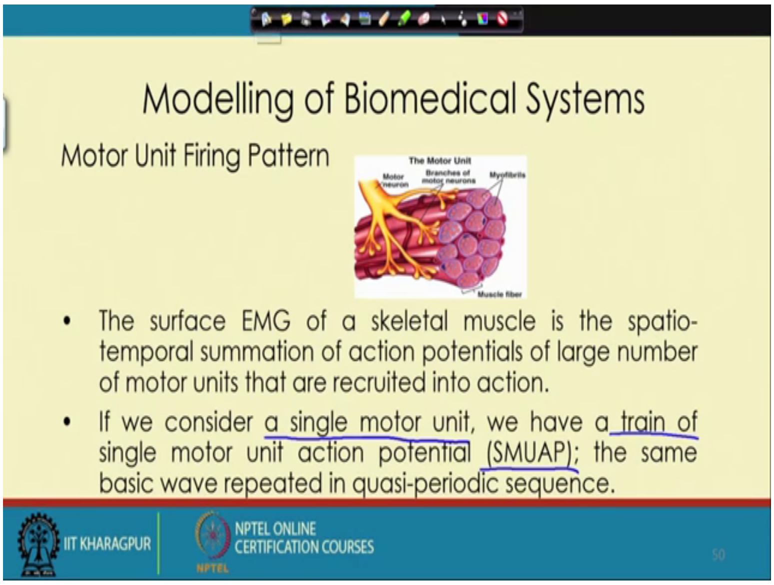

And in this particular case we look for the modelling of the biometrics signals. So, first for that we look at that motor unit firing pattern. So, we are talking about the EMG signal; so, for any action we know we need to activate a number of actually now this muscle fibres and for that a number of actually neurones they need to come forward to give that signal and do excite them.

So, if we take a surface electron and collect that EMG signal that we will get not just the output of coming from the one actually that neurone, but a number of actually neurones they are exciting those muscles. So, we are getting a summation of the that all of them the spatiotemporal summation of those action potential we will get.

Now, if we are interested to look at one particular motor neuron; then we need to consider one single motor unit or those muscles which are connected with one motor neuron. And in that case what we see that those set of muscles or muscle fibre; they are excited again and again. So, there is a train of actually single ok. So, train of single that which gives rise to that that single motor unit action potential ok.

So, this is we can take a unit in our case and what we get that this is a quasi periodic sequence; what we mean by quasi periodic? That it is actually getting repeated and it is not exactly periodic because a periodicity is varying, but that variation is not much it is within a band ok. So, that is why we call this as a quasi periodic sequence this pulse tense which are exciting the that muscles.

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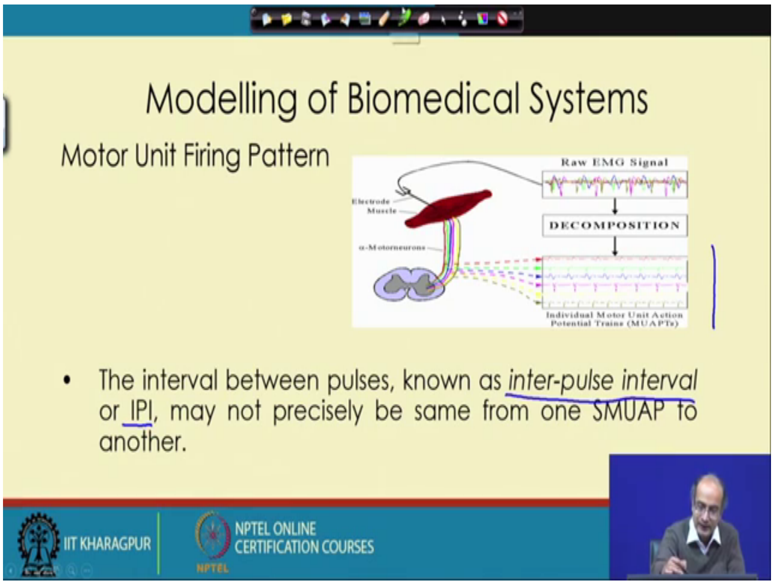

Now, let us look further that the interval between here we are showing first at the top that if this could be decomposed. Then we could get actually the signal coming out of each of these different fibres ok. So, we could get them separately, but it is not happening in that way we are as we are using a surface electron. So, we are getting or (Refer Time: 11:03) going near to that it is getting the some of actually all of them.

Now, if we look at that those signals because they are excited by the single neurone; they are excited at the same time and those pulses which are exciting those muscles they are occurring at the same time that is visible in that way and the interval between these pulses known as inter pulse interval or in short IPI. It is not actually very definite or does not remain exactly the same that is why we told it is quasi periodic ok.

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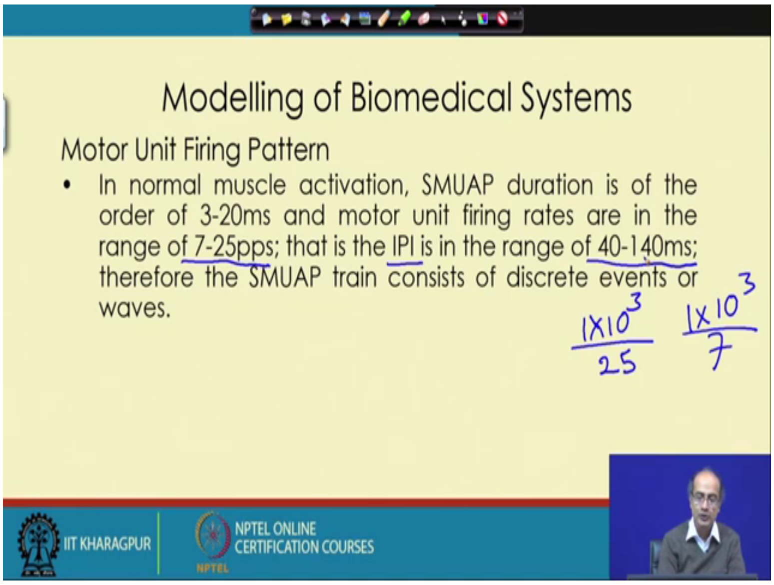

And if we look at them we find there is. a band within that it varies for the normal muscle activation that SMUAP duration it is in between 3 to 20 millisecond; that means, that event is occurring between 3 to 20 millisecond that much time those that skeletal muscles are activated and motor unit firing rate they are between 7 to 25 pulse per second in short pps.

What; that means, that the inter pulse interval or IPI corresponding to that 17 to 25 pulse per second; it is giving us 40 to 140 millisecond inter pulse interval ok. So, how we are getting that? In fact, 1 into 10 to the power 3 because it is a millisecond divided by 25 will give us 40 millisecond ok. Same way if we take that 7 that that same way we can get with the help of 7 that 1 into 10 to the power 3 by 7 we will get some number close to 140 ok.

So, they are having exact same amount of information it is just for the sake of our actually understanding and visualisation we can use one of them either inter pulse interval or the firing rate. In this case we find inter pulse interval is easier to visualise that event.

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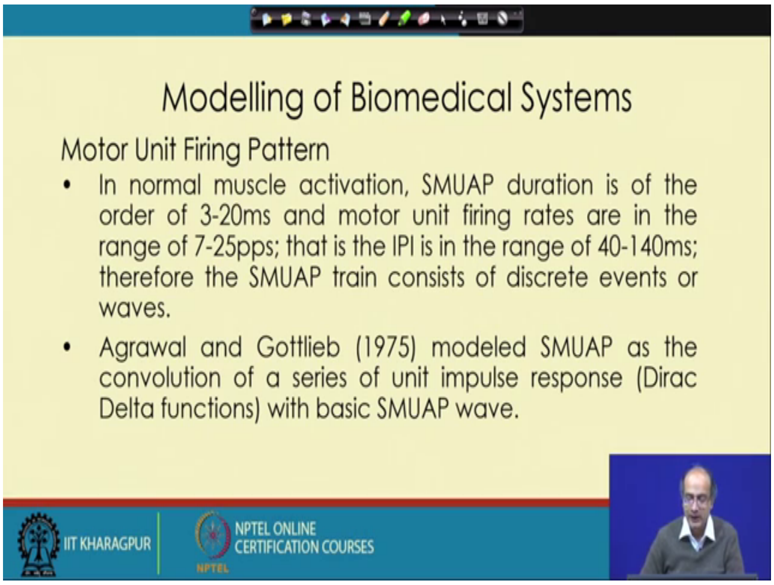

Now, two researchers we get Agrawal and Gottlieb they have model that SMUAP as the convolution of a series of unit impulse response. Because it is a train of pulses what they are suggested that it can be taken as a series of unit impulse and that whatever we are getting as that is not exactly looking like an impulse. So, it must be convolved with a basic shape which gives rise to the basic SMUAP wave.

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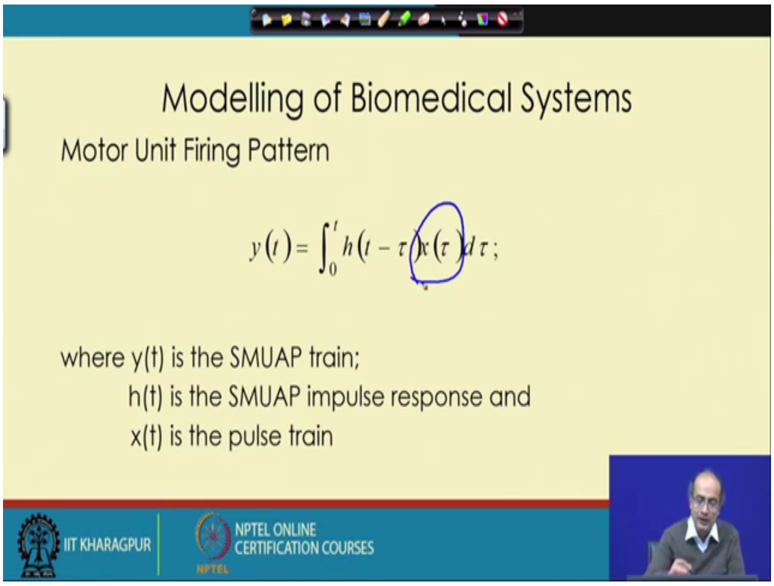

So, they have proposed a model in this way where y t is the SMUAP train and this is created by that pulse interval x t and that is the x t is the train of pulses and h t is the impulse response of a SMUAP impulses response ok. So, two together it is giving us the output y t that is what we have collected from the that that little electron or we can say that our sensor. So, if we can do that deconvolution then we can actually get this x ok; so, that is one thing we get.

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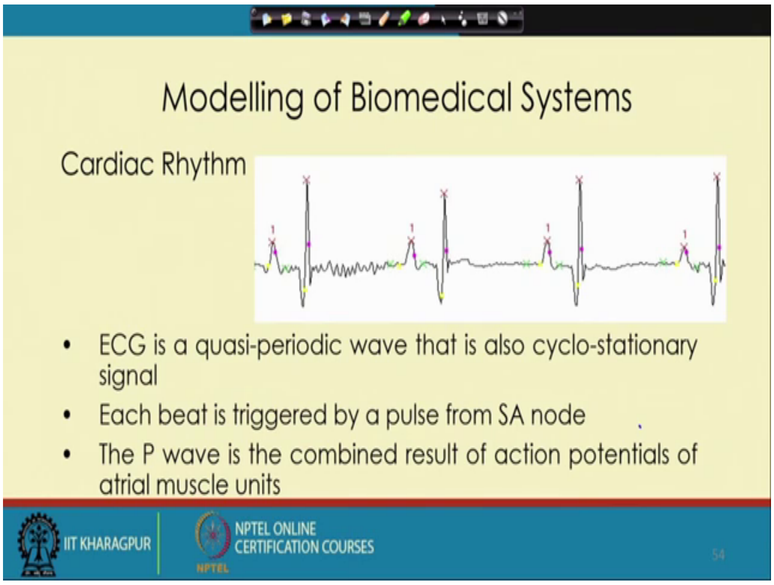

Next let us look at a different application altogether we have seen the cardiac rhythm. Again the cardiac signal or ECG it is not completely periodic, but it is quasi periodic; that means, say it is close to periodic signal and that is also a cyclo stationary single. What do we mean by cyclo stationary? If we compute the autocorrelation function; we see because of the that periodicity those autocorrelation functions are also becoming periodic. And when the autocorrelation functions become periodic then we call such signal as cyclo stationary ok.

So, that is a special property of the ECG signal. Now, each beat it is triggered by a pulse from the SA node we know more such nodes at there they are helping the SA node to give that message, but SA node is the lead in that ok. And first what we get the P wave it is the combination of the action potential of the atrial muscle unit the upper two chambers in the heart they are called atria. So, all the muscles together they get excited or they get contracted after getting the stimulus from the SA node. So, they gives rise to an action potential there that the total effect of that is recorded as a P wave.

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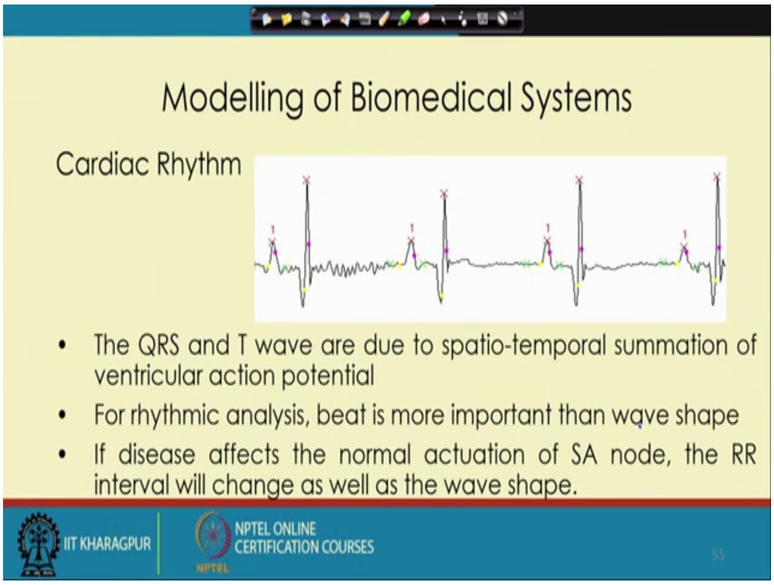

Now, after that comes the QRS and the T wave due to the spatiotemporal summation of the ventricular action potential. And we know to allow the activity that is the transfer of blood from the atria to the ventricles. SA node actually incorporates some delay in between or it actually stops the signal, but it is an attenuate it just stores the signal for some time and then after the time is over it releases that signal as such. And we get the first the QRS action potential because of the compression of the ventricular muscles and when they get relaxed or depolarised then we get actually the T wave.

Now, for some of the disease the rhythm or the beat are more important than the exact shapes. For example, whether the SA node is giving the signal in proper time or there are some nerves which are carrying the stimulus from the that AV node to the different parts of the ventricle.

So, whether that path way is intact or having some problem; so, all such cases that the rhythmic analysis or the beat analysis is good enough we do not have to look at the wave shape ok. So, rather than the wave shape if you look at the occurrence of the beat or that the time stamp or the difference between the two R waves which we call as RR interval that is actually good enough for that and the this kind of analysis ok. So, we get that at different points that if we just look at these impulses or trains train of impulses coming out of SA node that can give us a good amount of information about a number of diseases ok.

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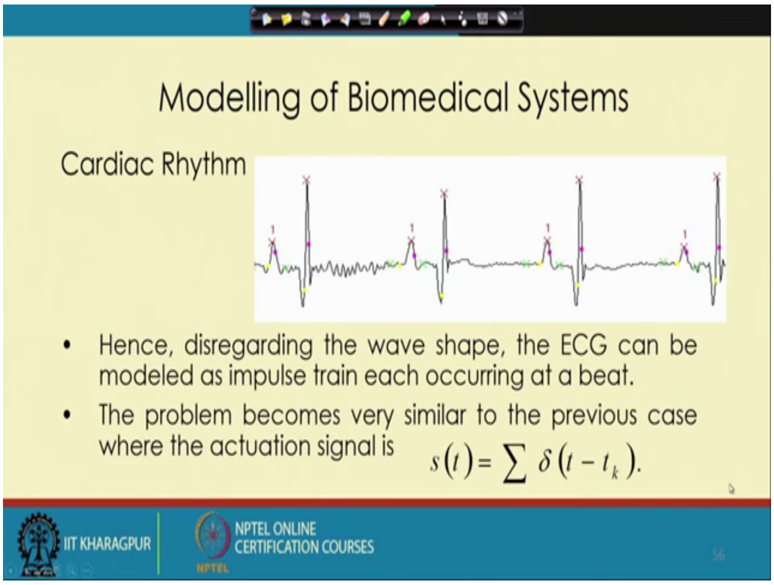

So, now let us look at further; so, hence for those kind of analysis what we can do we can disregard the wave shape of the ECG. And instead we can just look at the beats and then that our that intention becomes very similar to the previous case that we are looking at the actuating signal if they are coming at all if they are coming whether they are arriving at the right time ok; that becomes a crucial importance.

So, we get that that the this particular example of ECG; it has some commonality with the problem of the EMG we have just described earlier. So, again in this case the signal of interest is nothing, but some delayed pulses ok; so, that is our signal of interest.

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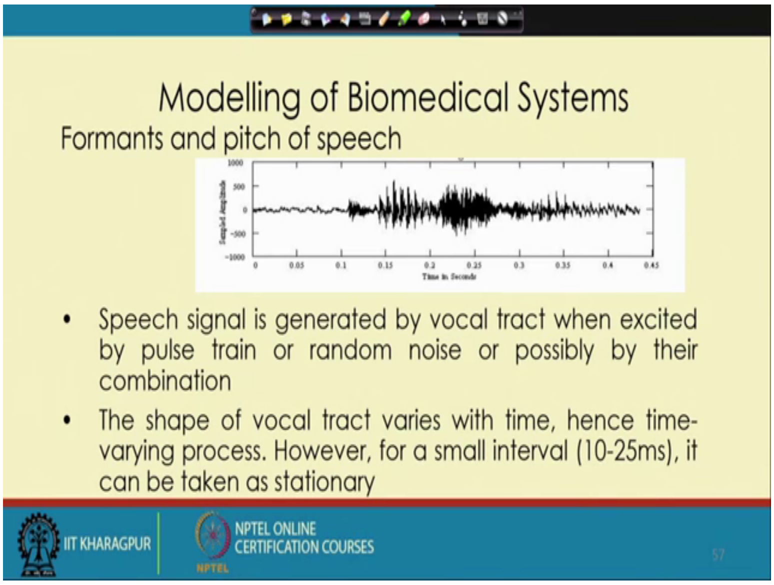

Next let us look at the speech signal we know the speech signal is generated by the vocal track and it has to be excited by actually the air which has a turbulent flow or we can what we can say that it is driven by say white noise like some of the statistical models actually we get given by noise. And other thing would be the the pulse train; so, these two separately or a combination of them can excite the vocal track and give rise to that signal ok.

So, here one thing we can note first that the shape of these vocal track they vary over the time, but this variation is slow. So, if we take a small interval of time the small interval could be between 10 to 25 millisecond depending on the different phonemes we are uttering we can say the vocal track shape remains to be the same and the signal remains to be a stationary within that interval; in other word its a quasi stationary kind of signal.

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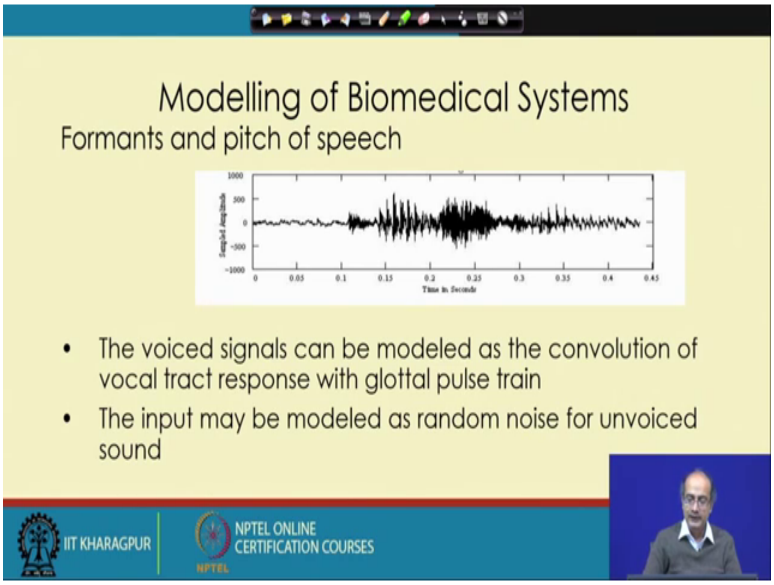

Now, when we look at the voice signal; it can be modelled as the convolution of the vocal track with the glottal pulse train. And when we look at that unvoiced single it is actually excited by the turbulent air flow coming out of the lung. So, as a mathematical model we can take at as it is given by a random noise.

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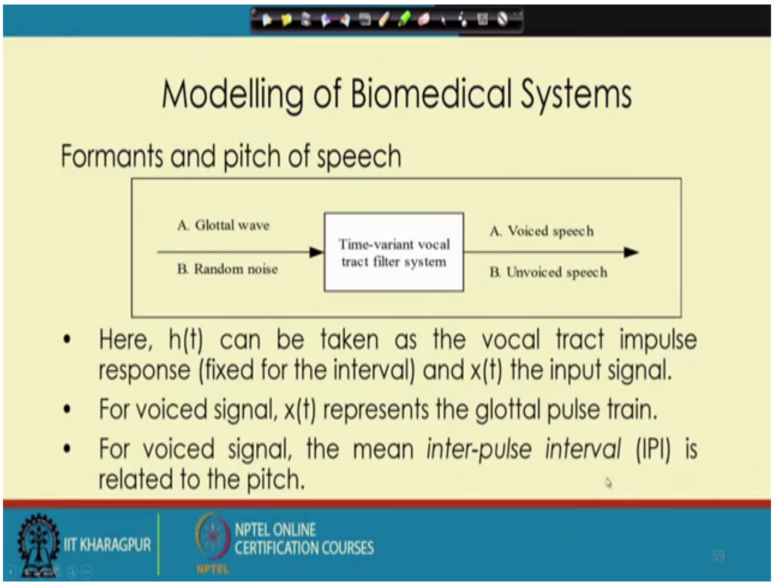

And that if we look at these kind of model; one thing we need to first get that whether it is random wave or random noise or the glottal pulse there is something common in these two. If we talk about random noise if it is white it is all the frequency content same way if we take that glottal wave that is can be represented again by some impulse train.

Now, if you take a single impulse the corresponding spectra we know that has all the frequencies present. So, in a sense it can be thought physically in this way that we can have two different kind of sources, but in that we have actually all the frequencies are present. And depending on that the vocal track transfer function we are allowing some of the frequencies to come in the output and we are suppressing some of them. And that gives rise to some output what we call as the voiced speech or unvoiced speech depending on that input signal whether it is a glottal wave or that random noise there is a the air coming out of the lung.

Now, here this transfer function h t that is we can say representing the vocal track impulse response and for that interval of 10 millisecond to 25 millisecond for that window of time it is fixed and x t is our input signal. For the glottal pulse we can take that it is a actually pulse train and again for the voice signal what we can tell that, there inter pulse interval that is related to the pitch or how often that glottal pulse are actually generated the difference between the two glottal pulse that is the inter pulse interval.

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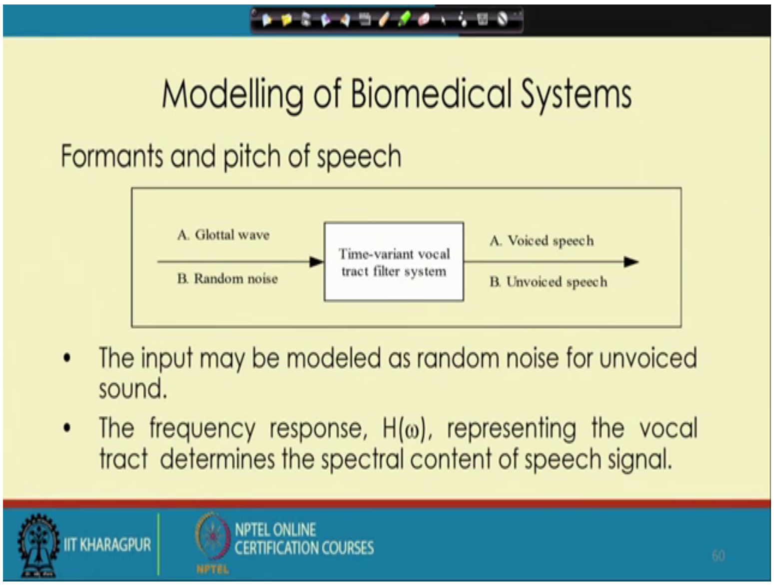

And this input may be modelled as that random noise for the unvoiced sound. And that the transfer function of that vocal track it can tell us a lot of thing, when you look at the utterances we see that many sounds they are pretty similar.

Let us consider the two sounds B and D for most of the part of the vocal track they are actually remain to be the vocal track shape remains to be the same; both are consonant sound. The difference between B and D is happening that in case of B that two lips actually coming together. So, that give rise to the sound B and when we are that uttering the word or the that word actually letter D for that phoneme the two lips they do not they come close to each other, they do not touch each other rather the tongue is actually moving at the end and giving the sound D.

In fact, if that you do not look at the video sometimes the B and the D; it can become actually difficult to distinguish. If the lipping of B can be given while the sound of D is played from the video the people may pick it up as B because we have seen the lip movement there ok. So, we can get actually that how the that vocal track shape is there and that can give us a lot of important information. For example, that when we are interested to identify the person that vocal track is something like our retina it gives us a unique actually map of that person. And whatever may be the utterance because its coming through that vocal track there would be some characteristics of that person.

The simplest thing we can look at that even in the source we can get for example, the pitch for the male and the female speech; we can easily find it out without any effort. The simple reason is that the pitch for the female voice is much higher than the male voice. So, by that we can actually very easily make the difference whether it is a female speech or a male speech.

And when we are actually taking a call over telephone even a old telephone or our friend calls through an unknown number that we cannot get actually their name in the mobile phone still from that voice we can immediately recognise that person. That is because the uniqueness of that vocal track of every person that is the reason just by listening to that voice, we can actually recall that person or identify that person very easily.

Now, we collect that enough motivation to model all such signal in a unified framework.

Thank you.