Optical Fiber Sensors
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Lecture 12
Noise Mitigation Techniques

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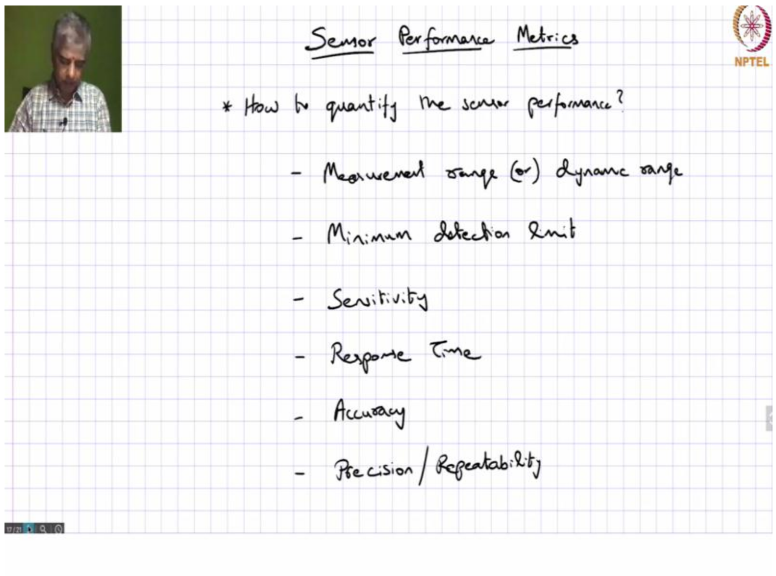

Hello, in our previous lecture, we looked at some of the Performance Metrics of Typical Optical Sensor. So, this is the quantification of the performance of an optical sensor. And we looked at you know several parameters like measurement range, minimum detection, limit sensitivity, response time accuracy and precision.

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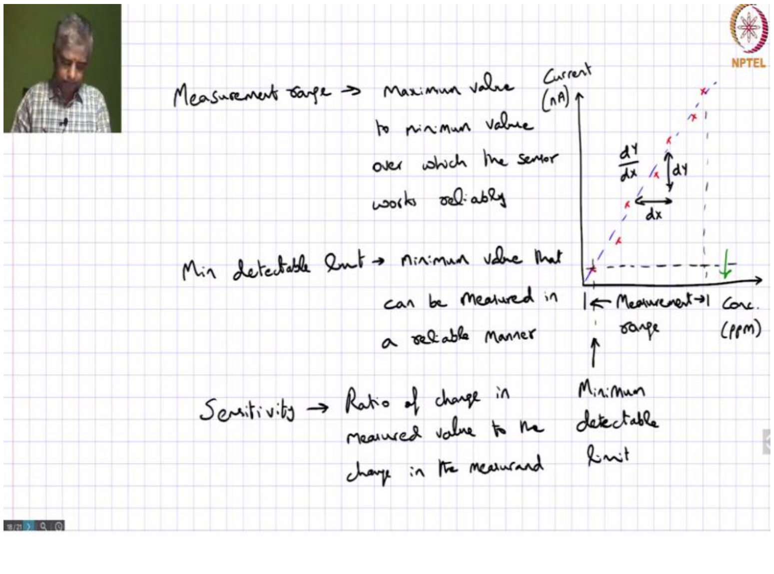

And specifically, when we are talking about minimum detection limit, we were saying that this minimum detection limit is limited by the noise in the optical sensor. So, so one of the questions is, can we possibly reduce this value of noise, so we can if we can bring down this value of noise, then you could possibly bring down the value of the minimum detectable limit also, so, you can move closer to 0.

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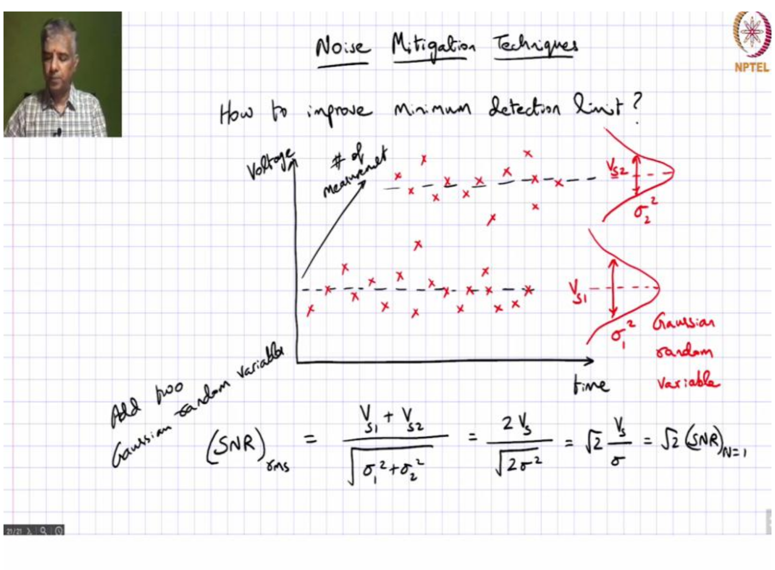

So, that brings up an interesting question, how do we deal with noise? How do you mitigate noise? So that is what we are going to be talking about. So let us ask ourselves the question how to improve minimum detection limit? So, what we are typically talking about is we were trying to see how we can reduce noise. So, let us look at this graph here, as a function of time, we are observing some current or maybe some voltage representing the measurement. So, when we look at this, the measured value maybe the measure end, maybe is holding at this value. But what we measure in our sensor is, it is something around that value, but not exactly that value.

So, we have, essentially, noise that adds on to the signal that we are trying to measure. So, your actual measurement might look something like this, maybe even some stray points like this and so on. So, you have a bunch of points around the actual value that you are trying to measure. So much so that if you take a histogram of all these points, that histogram is going to look something like this.

And it is, it is typically a Gaussian random variable, so this is Gaussian random variable, because the noise sources that we were looking at, typically all this short noise process, the thermal noise process, they APD multiplication noise, and so on. They are all characterized by Gaussian random process. So we know that this would correspond to some mean. So we can call that say, Vs is corresponding to the mean of all these samples, and it is also characterized by certain variance, which is what we were looking at previously as sigma square.

So that this variance and specifically the root of that, which is the RMS value, standard deviation, that standard deviation is going to be determining the minimum detectable limit. So if you want to improve that minimum detectable detection limit, you need to make this thinner, you need to reduced, reduced that sigma square as much as possible. And so that is, that is essentially the problem that we are going to look at.

So one way of potentially doing that is to do multiple sets of measurements. So you could, you could do one set of measurement like this. And so this is the number of measurement. So you could essentially do one more measurement, say, let us say the value of the measurement is staying the same, then you could do one more measurement, of course, what you are going to see is when you do these measurements, at different times, they are not necessarily going to replicate the noise is not going to replicate.

So, essentially, we are looking at this as another Gaussian random variable. Which will, once again show the same mean. So if we call this Vs1, let us call this Vs2, it is typically this same mean. And if we call the sigma 1 square, you get sigma 2 square over there. And since they, the noise characteristic is once again, it is broadband, white noise, additive white Gaussian noise is what we are looking at.

So the noise characteristics, do not change over multiple measurements. And because of that, if you look at the overall signal to noise ratio, we can add a multiple measurements, let us say we are adding these two measurements here. And then if you look at the signal to noise ratio, and let us say with respect to the RMS value of the signal, then that will correspond to you can add two Gaussian random variables, that is what we are doing.

And what we get in this case is Vs1 plus Vs2 the means add, and when it comes to the, the variance part, the variances add sigma 1 square plus sigma 2 square, but since we are defining everything with respect to the RMS value, you have to take a root of that. And when we look at this as the same sensor and the same measurement you are doing, so, your Vs1 and Vs2 are likely to be the same.

So, if you say Vs1 equal to Vs2 equal to Vs, then you can replace the numerator by 2 times Vs and similarly, the noise is going to be having the same characteristics or the same variance. So sigma 1 equal to sigma 2 equal to sigma, if you say then this is going to be root of 2 times sigma square. So, that is essentially root 2 times a sigma in the denominator and 2 times Vs in the numerator. So, what you essentially get is root 2 times Vs over sigma. And Vs over sigma what does that denote? That is the signal to noise ratio for when we just consider one set of measurements when n equal to 1.

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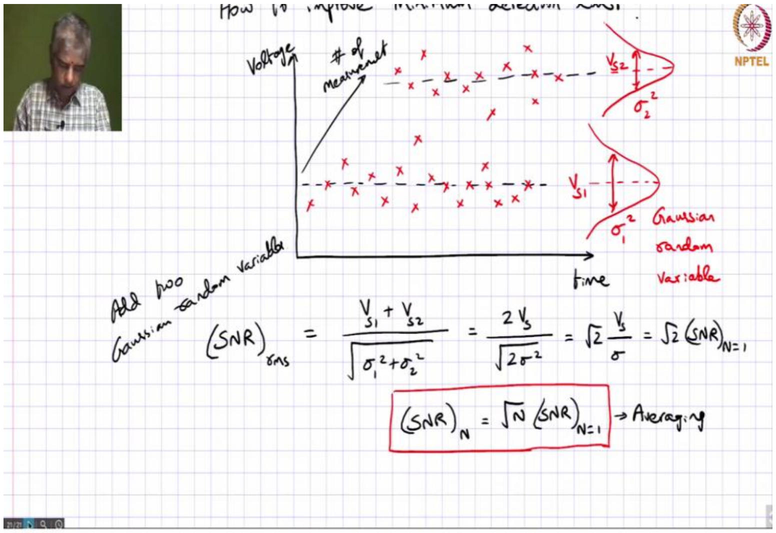

So, in general, what we see is your SNR RMS SNR of if you, you can extend this to N number of measurements. So, if you say the SNR that you get after n measurements, if you are adding all these corresponding samples, and then when you look at it, you essentially get, you can extend this and you can prove that this is corresponding to root times N compared to SNR of N equal to 1. So, that is a fairly powerful way of improving the signal to noise ratio of your optical sensor.

So you do N measurements and then through that you improve your signal to noise ratio. And this is a very powerful concept that is used in what we saw previously, at the beginning, we were just going through overview of the course. And at that time, we were talking about distributed fiber sensors and distributed fiber sensors, the amount of backscattered light is typically very low, so, it is corrupted by the noise, the optical receiver and because of that the signal to noise ratio is typically quite poor.

And to improve the signal to noise ratio, we are making use of the point that you could you send one pulse, you get backscatter trace, you wait until you collect all the samples from the farthest end of the, of your sensing fiber. And then you launch another pulse, and then you get the backscatter trace. So, essentially like this, you have multiple measurements that are done. And then you take the first sample of each of these traces, add them together, take the second sample, add them together, and so on.

And since these are all certain, the variation is because of some Gaussian random process, when you add, you get essentially, this sort of an improvement in the signal to noise ratio, the signal to noise ratio improvement with respect to one measurement is root of N. So, if you do, for example, 1000 or 100, let us say it is easier number. So, if you take, if you do 100 such measurements, then you get improvement in signal to noise ratio by a factor of 10.

So, it is quite, quite useful there. But mind you, one thing you are assuming is that the response of your, whatever perturbation you are trying to measure, that perturbation response is consistent over a period of time, over the period of time that you are taking to do all these measurements, it is not changing. Of course, what we have shown here is that it is it is holding at this value.

The let us say this is a gas concentration. So the gas concentration is holding at a steady value. If you are holding at that steady value, then you can, afford to do such averaging. So this is what we are calling as, through averaging you are essentially getting this improvement in the signal to noise ratio. So one thought is, can we do we have to do multiple sets of measurements? Can we possibly do this averaging across this timescale itself.

So, as long as each of these points are independent from each other, because it is only when they are independent you can do this, this sort of simplification here. So, that is when you get this improvement in the signal to noise ratio. So, as long as each of those points are independent from each other, you could possibly do an average across N samples. So, let us look at this in a separate page.

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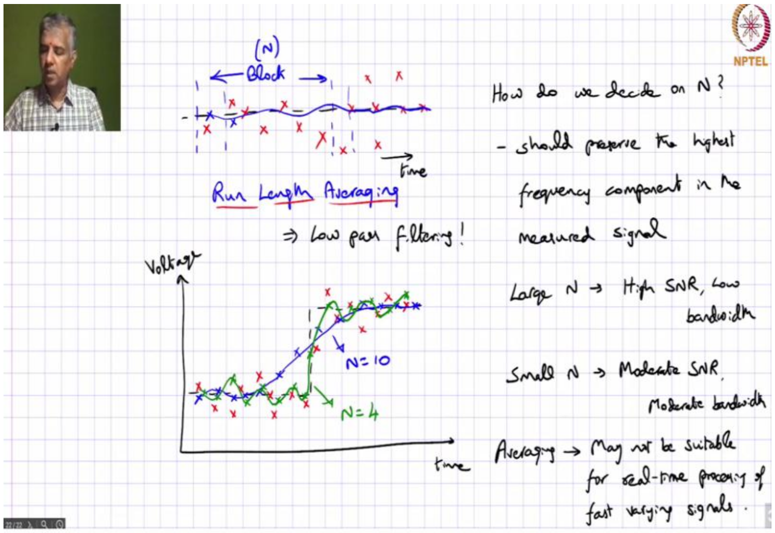

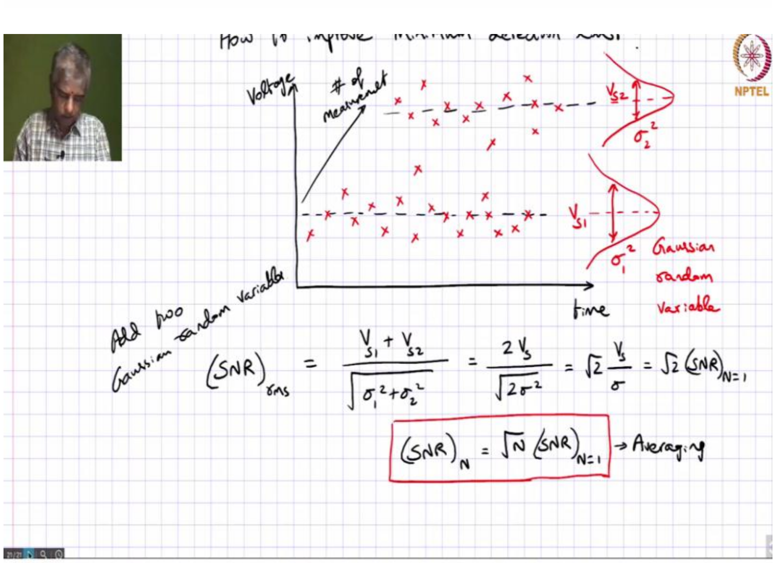

So, what we are talking about is your signal is holding at this level, now, as we talked about the noise samples maybe something like this. So it is varying with respect to time. And then what you could possibly do is to take a block of samples, so you say, okay I am going to take a block of so many samples. And across this block I will do an addition. If I do that, then you know if the mean value remains the same, so then it is the same expression that we saw were here the mean value remains the same.

But, but this, this each of these could potentially have this characterized by a certain random process. So, you could essentially get in get an improvement in this, in the signal to noise ratio, because of this. So, you would do let us say a mean of this and you would represent that by one point here and then you go to the next set of samples do mean of that and you get a representation like this and so on.

So, you can keep doing this and eventually what you will get is something that may look like this, that is closer to the value that you are trying to get. And, this is what you call us Run Length Averaging. So, the question is, can we, when can we do this random length average and the real question is how do we decide on, on the value of N? So, how do we decide on the value of N.

Where N is we are talking about the block of N samples that you are trying to trying to average. How do we decide on N? Well, in general, the principle that you want to keep is that your processed data, should preserve the highest frequency component in the measured signal, to preserve the highest frequency component in the measured signal. So far we have been looking at the value of the measure and being equal, I mean, we are being constant over, over time, because this is measured over time. What if it is not constant?

So let us say this is as a function of time, we are looking at this voltage. And just like before, we have certain level but after a certain time, it jumps to another level, whatever quantity that we are measuring, let us say the, like over the example that we took last lecture was gas concentration, let us say the gas concentration is suddenly jumping after a certain time. Now, in this case, when we look at the measured values, the measured values are going to be something like this, let us say.

And maybe measured value like here and then it is going to have some values at this other level. So now, what do you do? So if you employ this run length averaging, in this sort of a case and if you go with say, N equal to 10, so you are taking 10 samples 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and you are representing with one value. And then you take the next 10 samples, and you are represented another value and so on.

If you do that, then what you are likely to get something like this. So, you will have values closer to this, the ideal value that you are trying to measure, but as you approach this, as you start averaging across this, the average value is going to now change. So, it will go like, like this and then after a certain time it will be like this. So, essentially, what happens is when you are doing this you are, you end up smoothing this transition.

So, this is for N equal to 10. So, you say, N equal to 10 may not be a very good value, because it does not represent this transition very well. So, what do you do? Well, maybe I do not want to go to N equal to 10, maybe I can do N equal to 3 or 4, let us say N equal to 4. So, if you do N equal to 4, then you might get some value like this, like this, like this. So, since you are adding only lesser number of values, your signal to noise ratio improvement is not going to be as much as it is in the case of N equal to 10.

But what you gain in this process is that, the transition is relatively well preserved. So, you might have a signal like that, this is what you get for N equal to 4, but in this case the transition is relatively better sort of preserved. So, this is one of the key points to understand, essentially, what we are doing when we are doing run length averaging is you are doing what is called ow pass filtering.

So, you are essentially losing some of the high frequency spectral components in your signal. So, that is something you have to be vary of and if you want to extend the cutoff frequency of your low pass filter, so that you can bring in some of the high frequency components, you also start bringing in noise and because of that, you know, that the improvement in the signal to noise ratio may not be as high.

So that is something that you have to be very conscious about. So overall, so if we go back and look at this question, how do you decide on N. It is a trade off typically. So large N high SNR, your better SNR, but low, so what do you call low bandwidth, if you may call that because you are essentially smoothing over this transition, so lower bandwidth. Whereas, if you do small N then you get only moderate improvement in SNR, but moderate, so you get moderate bandwidth also.

But anytime you are doing this run length averaging, you are compromising on the bandwidth of your signal. So, your signal if you see the red things, the signal is responding quite quickly, but because of the run length averaging, you are starting to have this roll off around that transition. So, you are compromising the bandwidth in this case. So, that is important to understand. So, so, what do we learn from this overall, so averaging overall may not be suitable for applications where you need real time processing of fast varying signals. So, it may not be suitable for real time processing of fast varying signals.

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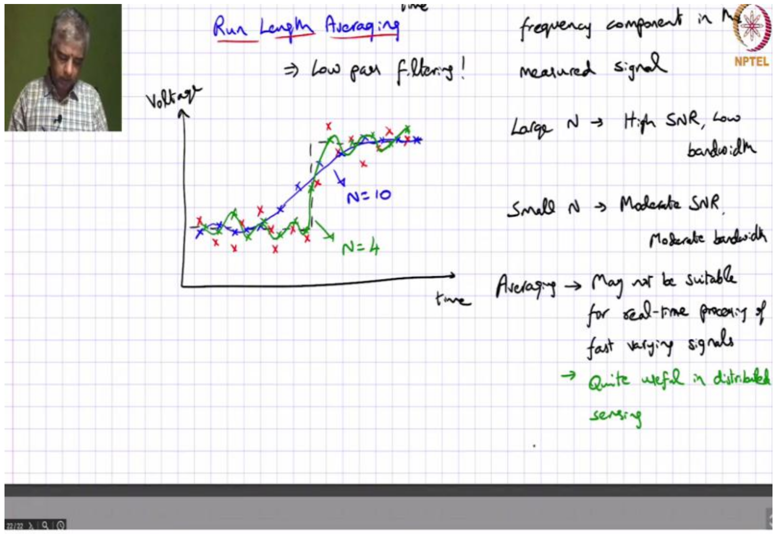

But nevertheless, the it could be quite useful in distributed sensing of, for example, civil structures. In distributed sensors in civil structures, if we are trying to pick up strain or temperature, those things change over much longer timescales, something in the order of seconds or even minutes, so you have that much more time to capture your signal and improve your signal to noise ratio.

So, in those cases, this is a very, very useful tool, it is quite useful in distributed sensing, where, where the, whatever you are measuring is not changing, much quickly with respect to time. So, that is an important thing to remember, realize. So, saying, that averaging in when you use averaging is, when you can afford to make multiple measurements and improve your signal to noise ratio through that. So, that is about averaging. So now, let us go on to looking at another tool that may be available to you as far as improving your signal to noise ratio is concerned.

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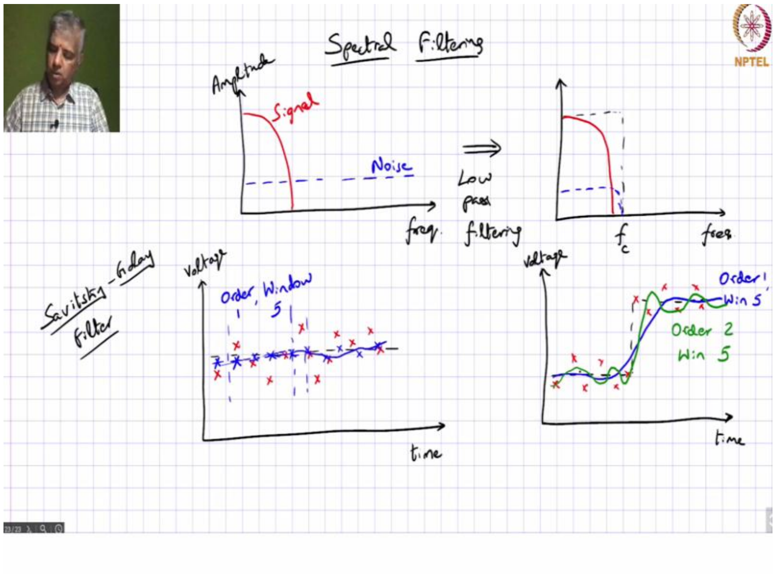

And that tool is Spectral Filtering. When you look at the signals, that you want to typically pick up using a sensor, in a lot of cases, you have the signal bandwidth. So if you are looking at this the spectrum of the signal, so this is amplitude as a function of frequency. If you look at the spectrum of the signal, that signal spectrum maybe something like this, it is only available. It is confined to certain range of frequencies.

Whereas if you think about noise that you have, that noise is spread across, it is like we talked about, it is typically white noise. So it is spread across all these frequencies. So this is noise and this is your signal. If that is the case, then why do we need to have receiver with very high bandwidth, I mean, your photodiodes normally are having the bandwidth in the order of 100s of megahertz easily, and so your receiver, your trans-impedance amplifier could also support 10s of megahertz of bandwidth.

Why do you need to have such a large bandwidth? When your signal is, let us say you are picking up some environmentally changing parameter like strain or temperature, humidity and so on, those signals are not changing very fast, they are typically having all the components within kilo hertz of bandwidth. So, so the question is, if this is the case, then what you could possibly do is, you could do low pass filtering.

So if you do low pass filtering, essentially, we are saying that we apply a filter that cuts things off at a certain frequency, let us say fc is the cutoff of your low pass filter. Now, of course, fc is typically like a corner frequency and then there is a very gentle roll off of the filter response. So, there are issues related to this how sharp the roll off you need, if you need a higher, if you need a sharper roll off, you need to go to a higher order filter and so on.

So, there are there are other issues, I am not going to go into details of those. But the key point here is, this may be enough to sort of preserve your signal which is only within this region. And the advantage here is that your noise now is also limited only over this region. So you are essentially improving your signal to noise ratio. So that is a reasonably easy concept to understand.

So you could do spectral filtering, if you know that your, the signals that you are trying to capture have only information content over well defined band of frequencies, so in that case, you could just take out, send it through a filter that allows only those frequencies, so in which case, you are also reducing the noise and thereby, you are improving your signal to noise ratio. So let us look at an example of one such filter.

So, I will take the example of filter that we use widely in our laboratory which is called Savitzky Golay Filter. And if I once I, once I tell you how we do this, then you will understand why we are picking up this particular filter. Now, of course there are lots of other filters; Vessel (()) (34:53), you name it, (()) (34:54). There is so many other filters that are already existing so you could look at any one of those things, but I am just taking one example of that.

So let us say the signal once again, that you want to measure is something like this, it is, let us take the easy case first where the quantity that you are measuring is not changing with respect to time. So this is once again, the voltage as a function of time. So what does the Savitzky Golay Filter do? Well, as before we have all these samples, so there are these noisy type of samples, something like this.

What you define in a Savitzky Golay filter, it is, in some ways, similar to run length averaging, in the sense that you are defining a block. So you would say, I am taking a block of five samples. What do you have to define for the filter is, you have an order, an order of the filter and you have window size. So in this case, we are doing over five samples. So let us say that corresponds to a window size of 5. And I am going to do order 1, if we do order 1, that is a first order polynomial. So that is just a simple straight line fit.

So what it is going to do is try to take these five samples and do a fit, a straight line fit. So if we do that, it might get something like this. And once we have that, then what it does is, it replaces this sample with the fit value. Similarly, this is the same way we did it in run length averaging, it goes on to the next sample, so it takes the next five samples over here, and then it does one more fit across this. So this fit might look something like this.

And then correspondingly, the point that you get is replaced by this. So it keeps replacing all the samples with this fit value. And what function we fit is, determined by this order whether its first order, just a simple line, or if you go to 2, it is a quadratic function, go to 3, it is a cubic function and so on. So, you can you can define different orders. But if you do this, essentially, if you keep doing this, you will find that your signals are now hugging closer to your actual value that you want to measure.

So, you get an improvement in the signal to noise ratio. And that improvement is going to be more just like we saw in run length averaging, if you increase your window size, so then once again, the question is, what should be your window size? Do you always pick up order 1? And so on. And the answer to that is well depends on what is the expectation in terms of your frequency content in your signal. Now, if you say your signal voltage as a function of time, has got some high frequency components, let us say in this case, once again, we are talking about having this transition over here.

If you have such a transition in your signal, then you apply the same thing. So first of all, let us represent all these noisy data points. Then if you do this order 1 window 5 over here, it works very well in this region, but when it comes to this region, it will tend to, smooth over. So you might get, I am just going to draw the effect of that. So if you, if you do an order 1 window 5 type of things, it might look like this, but it might smoothen over here and then it might look like this. So this is for order 1 window 5.

In such a scenario, so you are losing some information over here. So you want to preserve that information. So what is the better filter to go for, maybe you can go for a second order filter. So if it is a second order filter, then it takes all these samples and does a parabola, it is a quadratic fit to this and then replaces the sample and so on. And when it comes to this transition, you can still do a quadratic fit over this as long as it is just going one way, it should be fine.

So, or if you really want to preserve this thing, you can go to a cubic fit, that may be even better, since that it preserves this. But what is the downside of this, if you do, for example, the quadratic fit, the quadratic fit might start looking like this. So what you see here is the transition is better because we went to order 2 and we are still keeping a window size of 5, the transition is preserved better. But in this case, if you look at the signal to noise ratio, it is still not much better compared to what you started with. So, so that is, those are the kind of tradeoffs that you have to deal with while you are deploying some of these filters. Yes.

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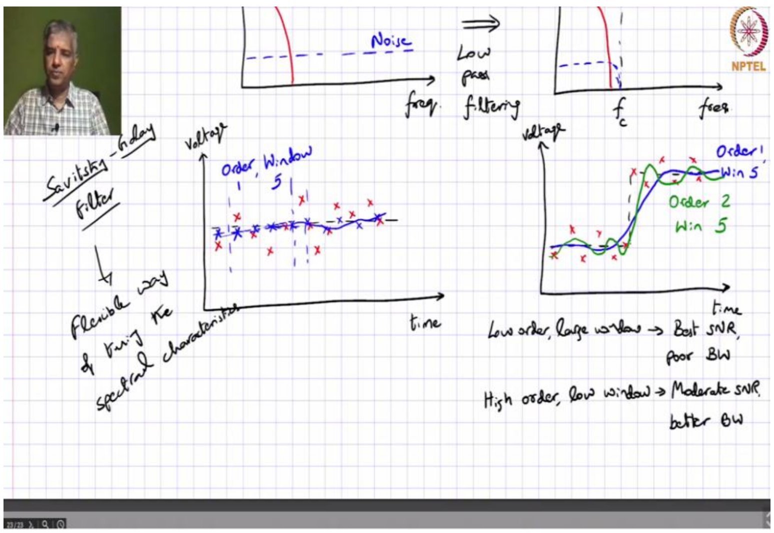

So, maybe you can just summarize what I said here. So, low order, large window you have best SNR improvement but poor bandwidth, whereas high order, you say low window size, then only a moderate improvement in SNR but better bandwidth. But the whole point is, this is, this Savitzky Golay Filter is a flexible way of tuning the spectral characteristics that are required. So flexible way of tuning the spectral characteristics required to process your signal. So that is a powerful way of doing an improvement in the signal to noise ratio.