Robotics and Control: Theory and Practice
Prof. Felix Orlando
Department of Electrical Engineering
Indian Institute of Technology, Roorkee

Lecture – 30
Neural Control of a Hand Exoskeleton Based on Subject Intention

Good morning, today we are going to see about the lecture on Neural Control of a Hand Exoskeleton Based on Subjects Intension; that is human subjects thinking or intention. The organization of today's lecture will be as follows, development of a learning scheme using surface EMG signal; that is development of a brain computer interface or muscle computer interface. And, the development of a learning scheme using surface EEG that is the next level.

The first level is forming mu CI; that is muscle computer interface and then BCI that is developing a learning scheme based on the surface electroencephalogram signal. And, then we see after that we see the working demos corresponding to both the mu CI as well as the BCI.

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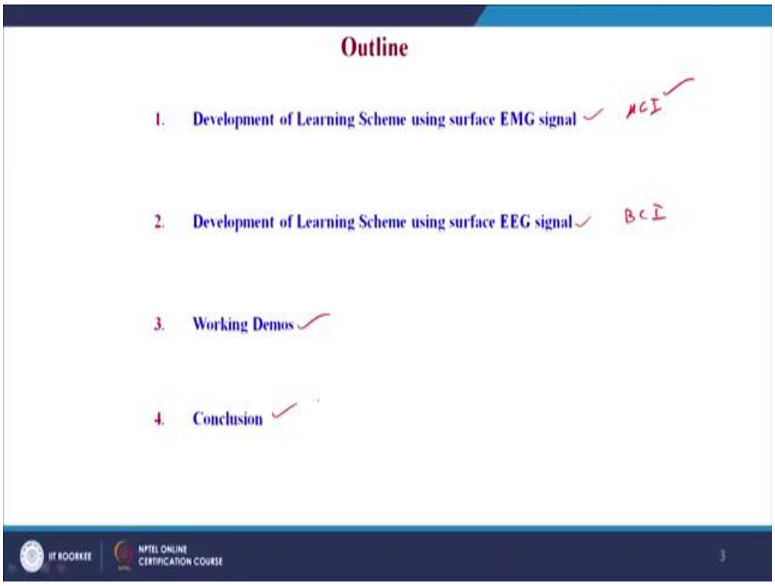

And then finally, we conclude our lecture based on the performance.

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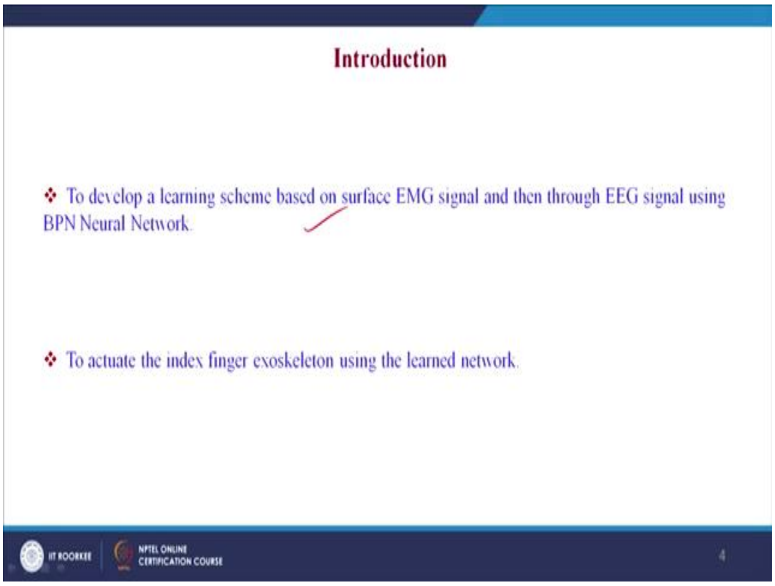

Now, coming to the introduction, as I said that the objective of this work is to develop a learning scheme based on surface electromyogram signal. And, then through electro encephalogram signal using back propagation neural network which is the feed forward network; so, that the future tasks will be to compare this with the feedback networks such as the recurrent network.

So, thereafter the development of this such learning scheme under the subjects intention is to actuate the index finger exoskeleton using the learned network; that is to actuate the network, actuate the index finger exoskeleton, we just to focus with the index finger exoskeleton with the other digits of the human hand being fixed.

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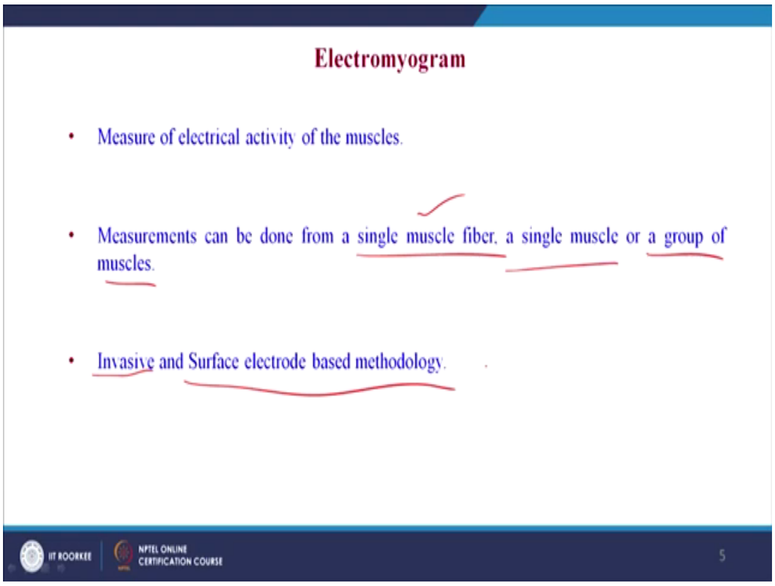

Now, coming to the electromyogram EMG; it is nothing but the measure of the electrical activity of the muscles. Measurements can be done from a single muscle fiber a single muscle or a group of muscles. Now, for the single muscle fiber and a single muscle the approach is called invasive method; that means, you have to penetrate through needles in order to reach that single particular muscle or the muscle fiber. Whereas, the signal or the measurement can be done, the recording can be done from a group of muscles.

And, hence that approach is classified as surface electrode based approach. Thus, the recording of the bio signals can be done by two ways; one by the invasive which is piercing through the human flesh in order to reach that particular muscle or the muscle fiber and record the signal. And, the other one is surface electrode based method; that is these electrodes are placed on or a fixed on the surface of the human subject in order to get the signal corresponding to that electrode that is either what is our objective either to record the muscle signal or the brain signal.

Accordingly, the surface electrodes are placed on the muscles or on the scalp in order to record the signals. Thus it is recorded from a group of muscles.

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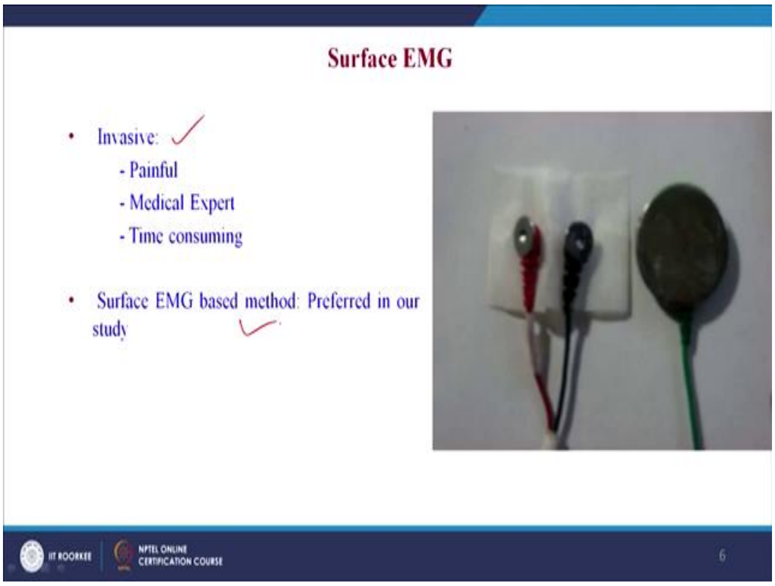

Now, coming to the surface EMG electrode; so, this method is preferred in our study but it has many limitations also. First of all let me put forward the limitations associated with the invasive approach, it is quite painful and it requires the medical expert to get into our work or in our loop in order to help us where to insert the needle in to obtain the proper signal. Because, it is going to harm the subject that is why we need a medical expert human being to be in the loop of our experiment and it is quite time consuming as well.

And now coming to the surface EMG based method, that is the reason why we go for the surface EMG method; because these limitations can be overcome by this surface EMG based method. But there are also limitations associated with surface EMG based method they are: it varies from subject to subject. Second point is if the same subject is taking depending on his mood the signal gets varied high non-linearity compared to that of the invasive approach. So, these are the electrodes which are plus minus as well as the ground electrode.

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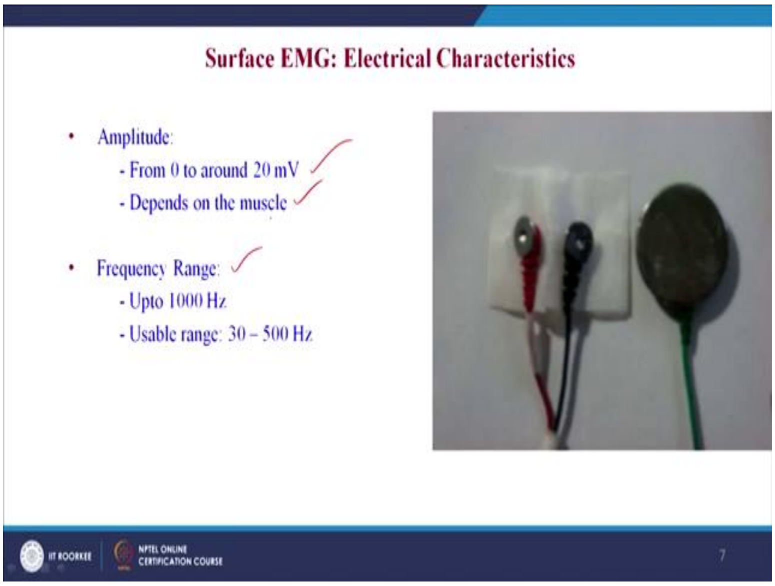

Now, coming to the amplitude associated with the surface EMG; that is the electrical characteristics or the amplitude is from 0 to around the 20 milli volt whereas, it depends on the muscle for this range. And the frequency range is up to 1000 Hertz and the usable range is between 30 to 500 Hertz.

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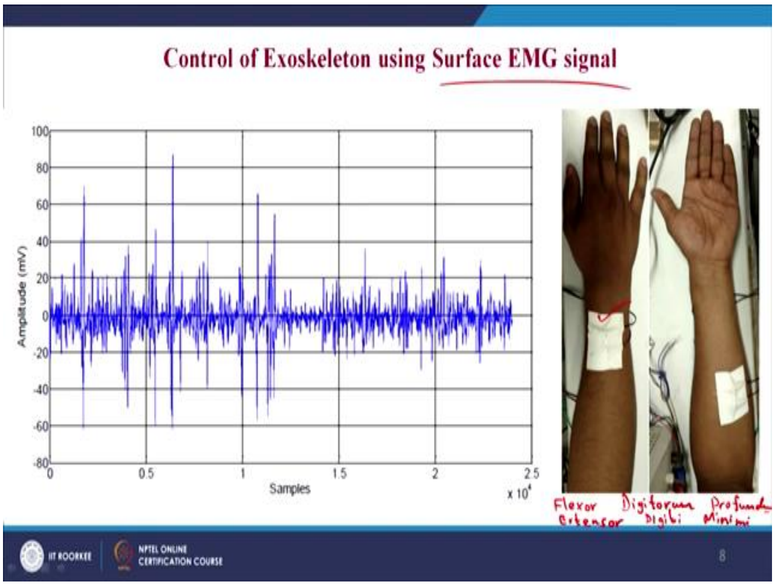

Now, coming to the control that is the open loop control you can see that is based on the surface EMG signal. So, these signals are obtained from the forum of the subject in order to get the signals corresponding to the extension where the electrodes are put on the extensors digiti minimi muscle.

In order to get the extension signal, the signal corresponding to the extension we put the electrode on the forearm mostly in the dorsal side you can say that is on the extensor digiti minimi muscle. And for the flexion part we put on the forearm pertaining to the palmer side which is on targeting the muscle named as flexor digitorum profundus. So, the two muscles we have considered in our study or flexor digitorum profundus and extensor digiti minimi.

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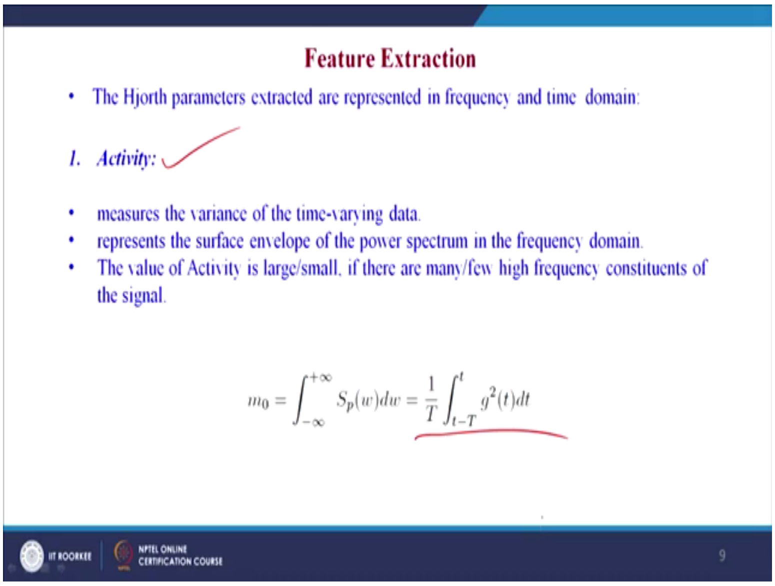

So, the schematic shows here, the signal collected in one window of the signal collection; that is for 5 second we have collected the window in the signal, here corresponding to this finger motion or monitoring extension and flexion of the finger index finger we have taken the signal which is shown here schematically. And coming to the feature extraction so, what are the features getting extracted after the signal comes to us after proper processing of it.

So, the signal is first of all filtered and from the filtered signal we have extracted the features which are nothing but the Hjorth parameters and also the RMS value of the signal. So, now, let me specify what are the Hjorth parameters; they are extracted in frequency as well as in domain frequency time domain. So, first one is called the activity there are three features of the Hjorth parameters; they are called activity, mobility and complexity. So, activity basically it is the measure of the variance of the time varying data.

It represents the surface envelope of the power spectrum in the frequency domain. The value of activity is larger or small if there are many a few high frequency constituents of the signal. So, it is given in this expression which is $= \frac{1}{T}\int_{t-T}^{t}\left(\frac{dg}{dt}\right)^2 dt$ because the variance of the time varying signal.

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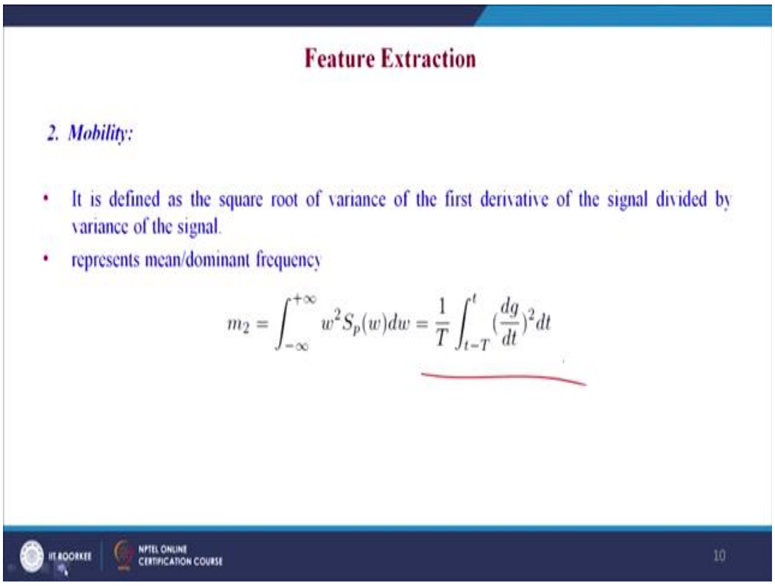

Whereas, the mobility is the first derivative of the activity and it is different like this square root of the variance of the first derivative of the signal divided by the variance of this signal, which is given by this expression. And it represents the mean or dominant frequency.

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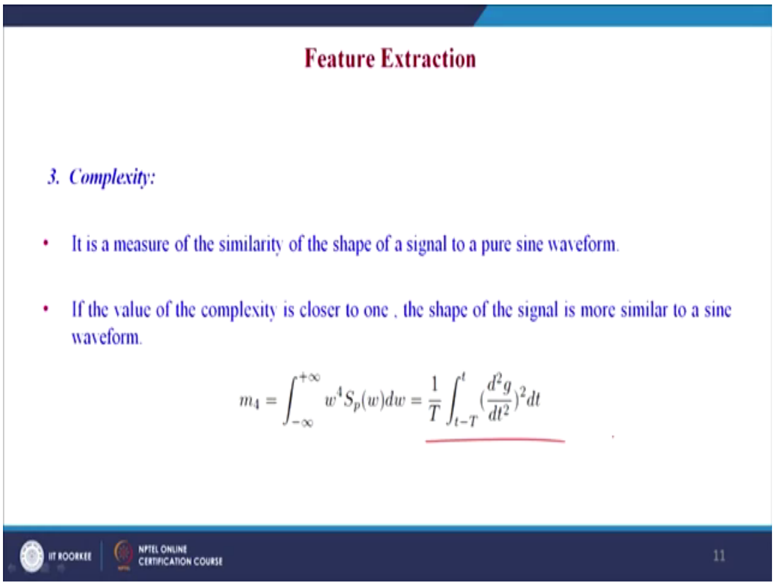

Coming to the complexity which is nothing but the second derivative of the activity and it is a measure of the similarity of the shape of a signal to a pure sine waveform. If this value of the complexity is close to one; the shape of the signal is more similar to a sine signal and this is given by this expression which is $= \frac{1}{T}\int_{t-T}^{t}\left(\frac{d^2g}{dt^2}\right)^2 dt$.

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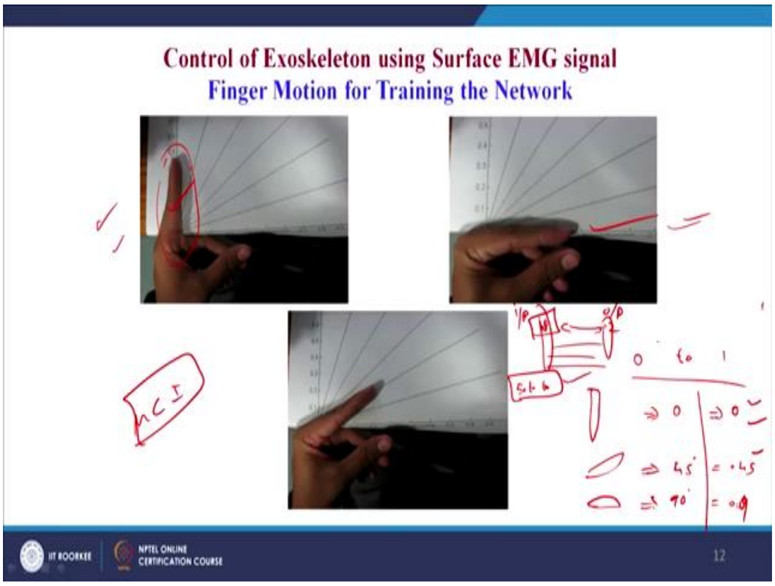

Now, coming to the experiment what we have done in order to have the system getting trained by the for feed forward neural network; in order to have the open loop control in order to given in order to trace the given joint angle. So, the finger motion for the training for training the network is in such a way that, first the finger index finger of the subject is trained in such a way that yeah, angular map is pasted on the table is fixed on the table so that the subject human subject is made to generate the data based on the finger configurations or the finger postures.

First he kept the finger in the relaxed mode, which corresponds to the extension that corresponds to 0 degree and slowly he has to move with the 10-degree variation of the angle each time and get the corresponding joint angle pertaining to that. So, he knows it is 0 degree and this is 10 degree plus 20, 40, 20, 30 accordingly it goes from 0 to 90 degrees. And you know that the network gets the input as well as the output in the normalized ones.

So, we have normalized the input and output data to the range 0 to 1. So, we have made the subject to keep the fingers first in the relaxed mode and ask them to as a subject to move and keep it in the flexed mode. So, this is the in order to normalize the data between 0 to 1 we have taken the extreme data corresponding to extension and flexion of the human finger.

Then we as a subject to move so, that the muscle computer interface programming environment allows the subject to get the information to be put by him. In such a way that for corresponding finger joint angle he has to enter the joint angle that is a finger portion is kept here he has to enter 0; when the finger portion is kept here he has to enter as seeing the graphic can he enter it is 45 degrees. And, accordingly if the finger is in the flux to completely flux tone it is corresponding to 90 degree.

So, he will be entering 0 for this and 0.45 for this and 0.99 for this value. So, he has to enter that value and corresponding features or computed simultaneously with the sampling period of a power 5 millisecond; with that sampling period each time the features corresponding to the finger postures are computed by the muscle computer interface programming part. So, that muscle computer interface program part will compute the features that is their Hjorth the features along with the RMS value, it has four features and accordingly it can compute them for each posture of the finger.

Because the posture is determined by the human subject; he knows where he is keeping the finger on which angle that angle is nothing but the output value and the finger and the signal features are coming in the input. So, the pattern input and the output pattern which is the joint angle. So, this is the Hjorth perimeter feature corresponding to that what is the joint angle because it is 2 means it is kept in 20 degrees. So, pattern input and output pattern accordingly 50 to 60 patterns can be made in order to input output patterns can be generated in order to try in the feed forward network.

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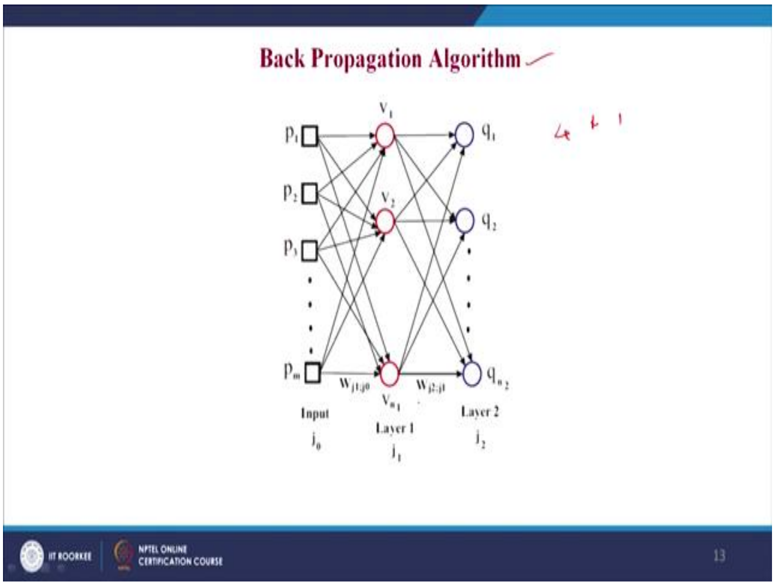

So, the feed forward network we have considered in our study is the back propagation network, where we have the two layer that is the input layer the hidden layer and the output layer. So, the hidden layer is only one hidden layer with the corresponding number of neurons being 20 in our study.

So, we have the 4 input parameters which are nothing but the 3 Hjorth parameters and 1 RMS value and the corresponding output is 1 output ok. It is basically the mapping from 4 to 1 that is a 1 joint angle corresponding to this 4 input parameter. And their weights connecting the input layer to the hidden layer 20 by $W_{j1\,j0}$; whereas, the weights connecting the hidden layer to the output layer are represented by $W_{j2\,j1}$.

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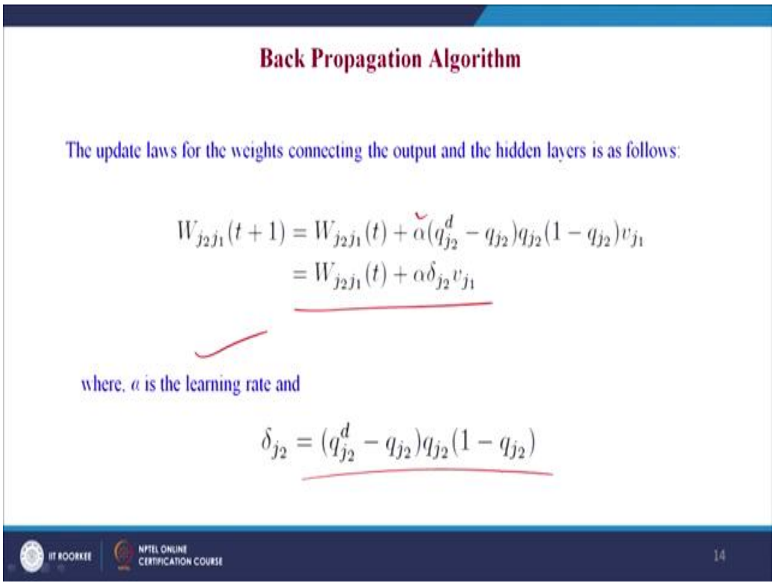

And, now the update lasts for the weights connecting the output and the hidden layer is given by

$$W_{j2j1}(t+1) = W_{j2j1}(t) + \alpha(q_{j2}^d - q_{j2})q_{j2}(1 - q_{j2})v_{j1}$$

And, it is simplified as this one there the δ where α is the learning rate and the δ_{j2} which is given by $\delta_{j2} = (q_{j2}^d - q_{j2})q_{j2}(1 - q_{j2})$ it is the error getting propagated from the output region to the hidden region.

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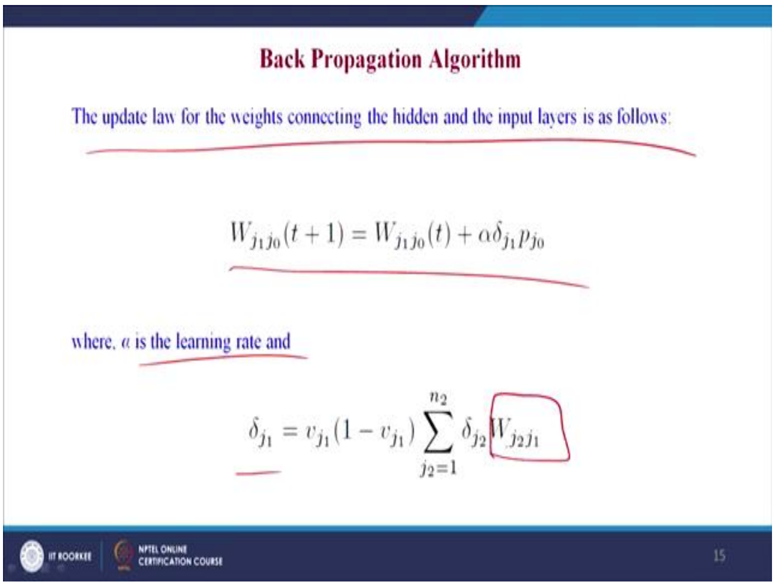

Similarly, now once the weights connecting the hidden to the output layer is k updated from the updated weight, we are going to update the weights connecting the hidden to the input layers; thus it is given by

$$W_{j1j0}(t+1) = W_{j1j0}(t) + \alpha\delta_{j1}p_{j0}$$

Where the α is the learning rate as you know and the propagating error is given by

$$\delta_{j1} = v_{j1}(1 - v_{j1})\sum_{j2=1}^{n_2}\delta_{j2}W_{j2j1}$$

which is the weights updated connecting the hidden and the output layer.

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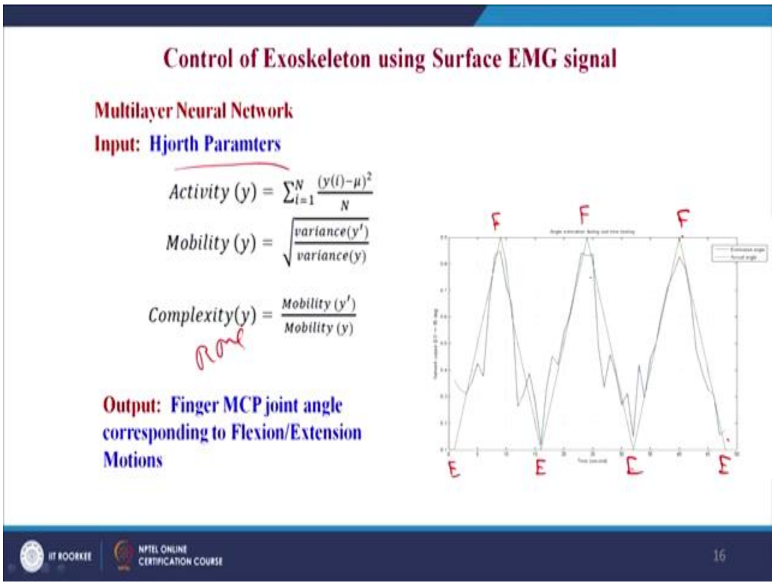

With this we have now the system getting trained with the input parameters input being Hjorth parameters along with the RMS value and the output is the fingers MCP joint; that is a first joint of the exoskeleton in order to have the corresponding flexion extension motions.

Thus, desired trajectory is to flex extend flex extend flex extend. So, this one is the extended and this flexed and this extended again the flexed configuration extended flexed and extended. So, based on these configurations on off on off; so, we have the trajectory of the neural network based predicted output is shown here with the blue line; that is the estimated joint angle the performance is shown here.

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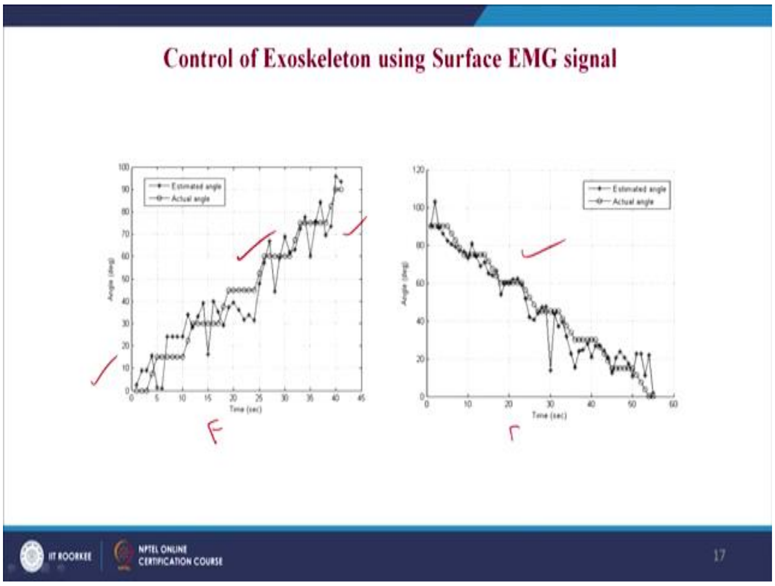

Accordingly, for the continuous almost continuous in between angle it is the performance obtained from the trained neural network. So, this is for flexion going with the 10-degree joint angle updation instead of going straight away from 0 to 90; we have moved in yeah almost continuous manner. And, we have obtained the performance based on our trained BPA network for this is the flexion woman and this is the extension case.

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And, the working demo corresponding to this trained network based exoskeleton is show here. So, now, we see the working demo of the muscle computer interface for the index finger exoskeleton based on the online recorded EMG signal, for the on and off control purpose. Again I will show you quickly.

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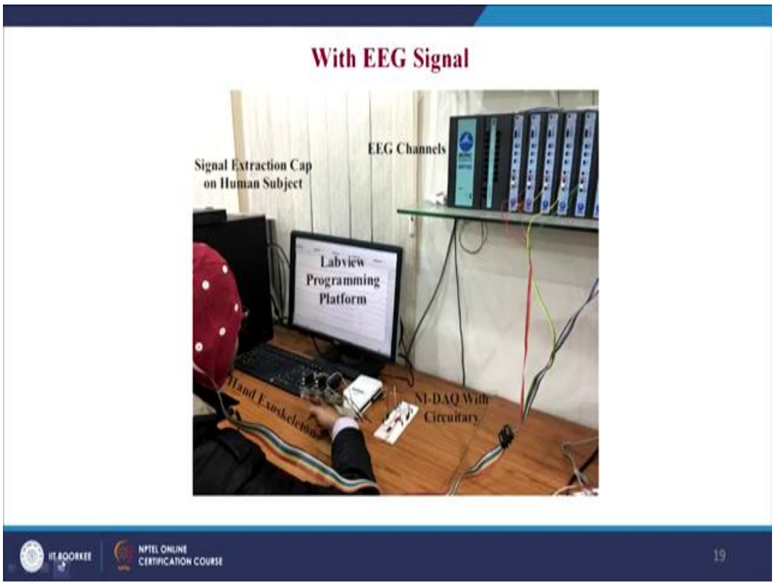

Next we have done the learning approach for the exoskeleton, involving the subject's intention with brain signal that is electroencephalogram signal. So, we have performed this in the lobby programming platform using a DAQ card interface as in the case of muscle computer interface.

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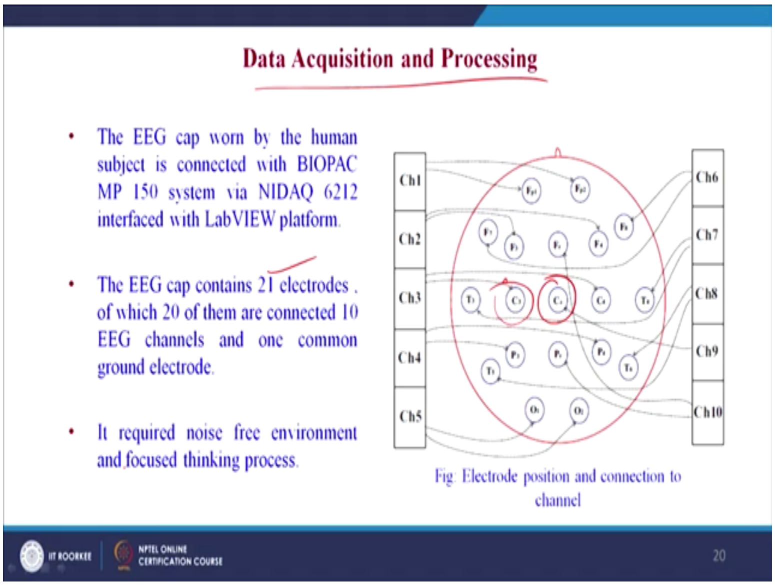

We have used a system which is basically the bio pack system, which is having nearly 28 channels out of which if we have utilized the channels 2 and C 2 and C 3; these two are the channels we have utilized in order to obtain the signals corresponding to the finger index finger motion.

So, the EEG cap the data acquisition first you start with the data acquisition processing EEG cap is one by the human subject is connected with a bio pack MP 150 system via the DAQ cards that is the national instruments DAQ cards interfaced with Lab VIEW platform. The EEG cap contains a total of 21 electrodes electrodes of which 20 of them are connected through 10 channels and 1 is the common ground and it required in noise free environment and hence in order to facilitate a focused thinking process of the subject.

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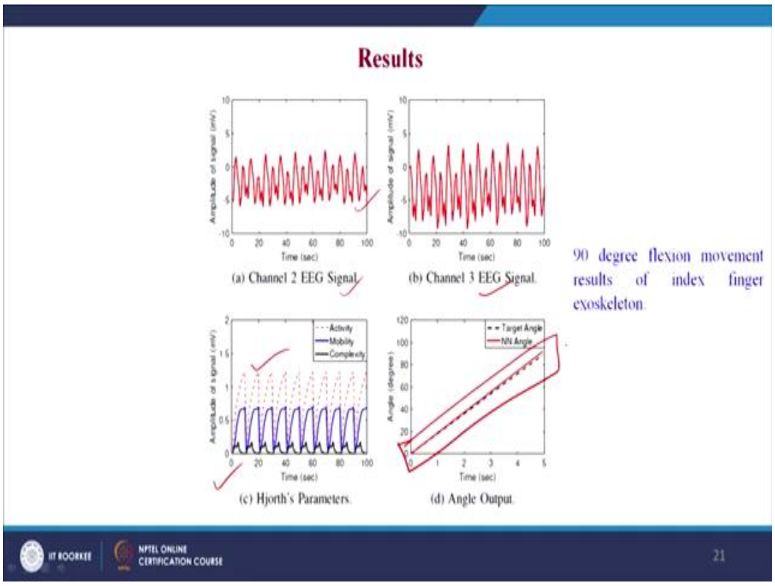

So, now we focus here only the results because in the same way we have trained the system as in the muscle computer interface. The same way we ask the subject to think and perform the training case. And accordingly the data has been generated and now we see the test result in such a way that the amplitude of the signal corresponding to the particular window is shown here for the 2 channels; channel 2 and channel 3.

And the output which corresponds to the flexion of the index finger is in such a way that the input Hjorth parameters are shown here. Where the activity mobility complexity profile is shown here where the activities magnitude is compared comparatively higher than that of the mobility and complexity whereas, the complexity value is much lesser compared to that of activity and mobility. So, the output in tracing the 90-degree joint angle of the finger is shown here, where the target angle is given by the dotted one and the network predicted angle is given by the red color one.

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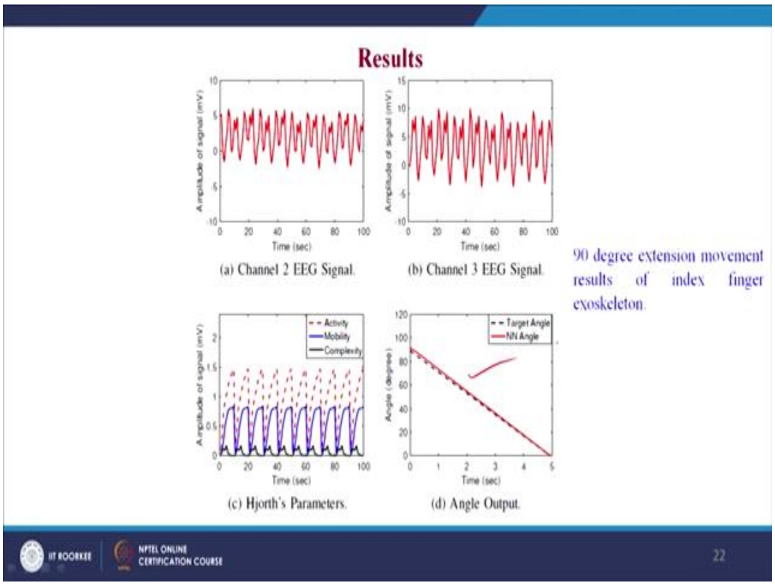

Similarly, with 90-degree extension motion that starts from 90 going towards 0 degree by a 90 degree flow is shown here; where the performance is better compared to the extension one number 2 the flexed one.

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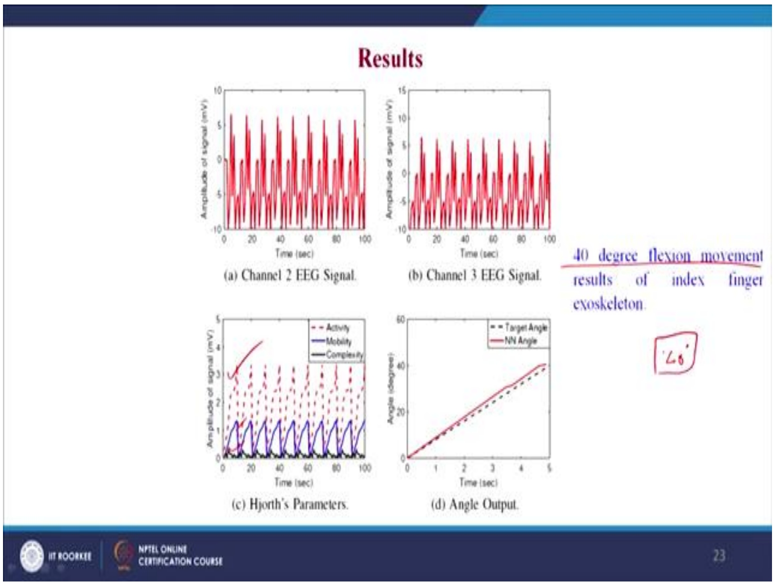

And similarly, here also got we have observed is both the magnitudes of act mobility and complexity or lesser than that of the higher value of activity feature. This is for 40 degrees of freedom flexion moment because the angle meant for flexion of the index finger is index finger actuator of the MCP joint is meant to be having 40 degree; that is why we trained first with 90 degree flexion extension and then with 40 degree to have the accurate mapping with that of the joint angle of the exoskeleton.

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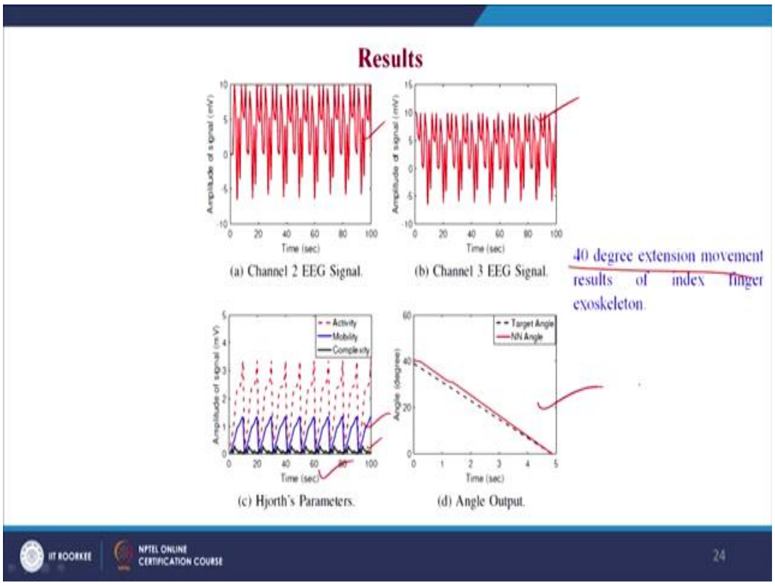

And, similarly this is the extension pertaining to 40-degree movement extension for the index finger exoskeleton. So, the online signal is shown here for both channel 2 and channel 3 for that particular window. And the corresponding input and output is in such a way that the Hjorth parameters having always the activity value being the non derivated value.

And, for the first derivative and the complexity being the second derivative having the values lesser than that of the activity in the terms of a blue color and the black color corresponds to mobility and complex with respectively and the joint angular matching or the performance is shown here for the 40 degrees extension motion.

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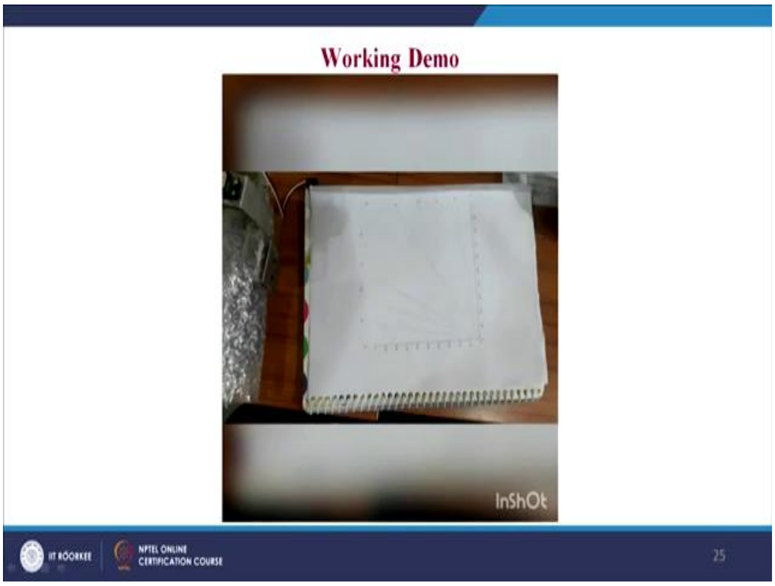

And now, we come to the final slide which is basically the working demo that corresponds to the subject intention with the brain signal alone. Why we go for BCI when compared to the muscle interface, when we have the muscle signals also not functioning the basic master signal what we have is the brain signal alone.

So, with the master brain signal alone, we try to do this rehabilitation paradigm in order to assist the patient who lost the control of the hand due to stroke. That is the working demo with the online recorded brain signal that is EEG signal is shown here. So, now we see the working demo of the exoskeleton based on subject's intention using only the brain signal, which is shown here for the index finger exoskeleton.

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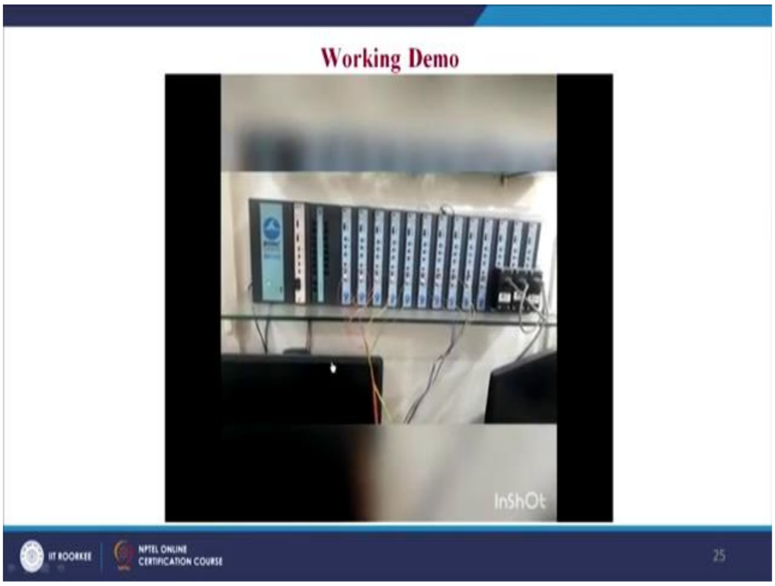

So, we have started with the same plot showing the joint angle of the subject.

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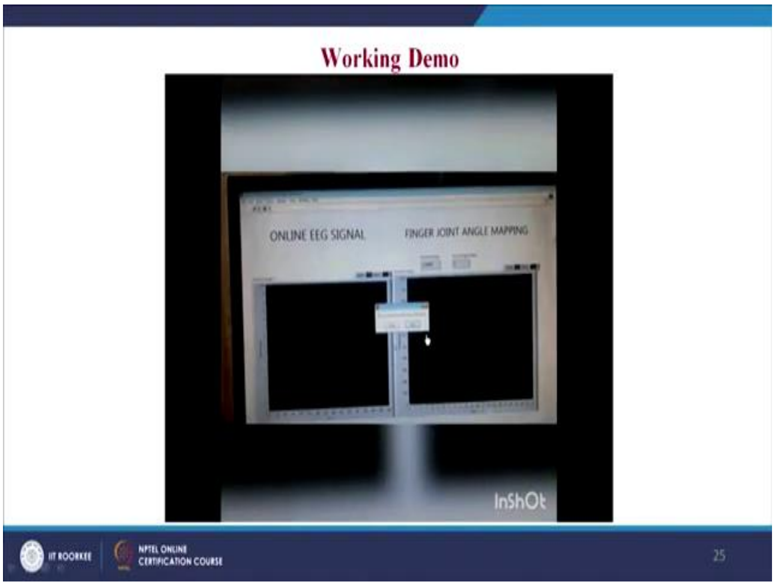

Accordingly the through the LabVIEW based NI DAQ interface. So, this is the muscle computer interface brain computer interface where the signal online is recorded.

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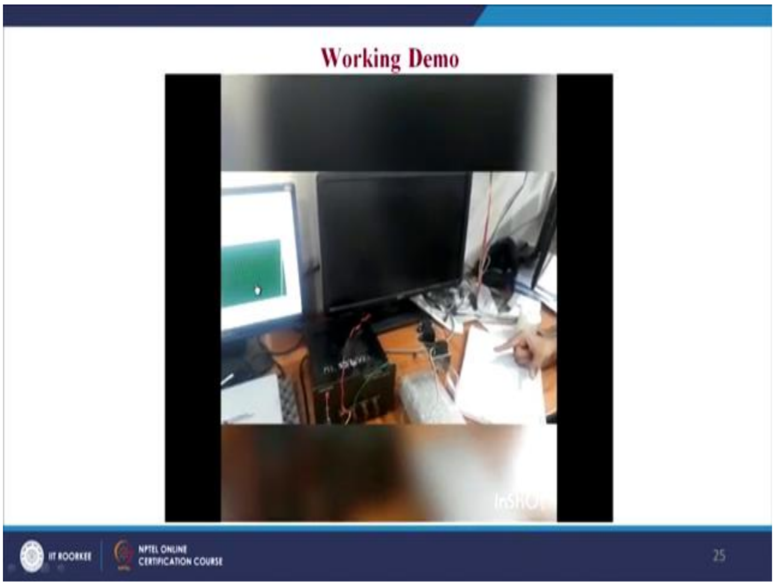

And this is this window shows, the online tracing of the desired signal by the actual signal that is the actual joint angle. So, that you can observed that the exoskeleton also has a 10-degree motion corresponding to the online recorded EEG signal.

So, the traced signal in the graphical mode is shown here. So, that we start from extension going to flexion and then comes extension. So, this is how the performance is again we flex it. So, that the traced signal the obtained online recording signal, which also getting mapped with the joint angle corresponding to that of the features Hjorth parameter features.

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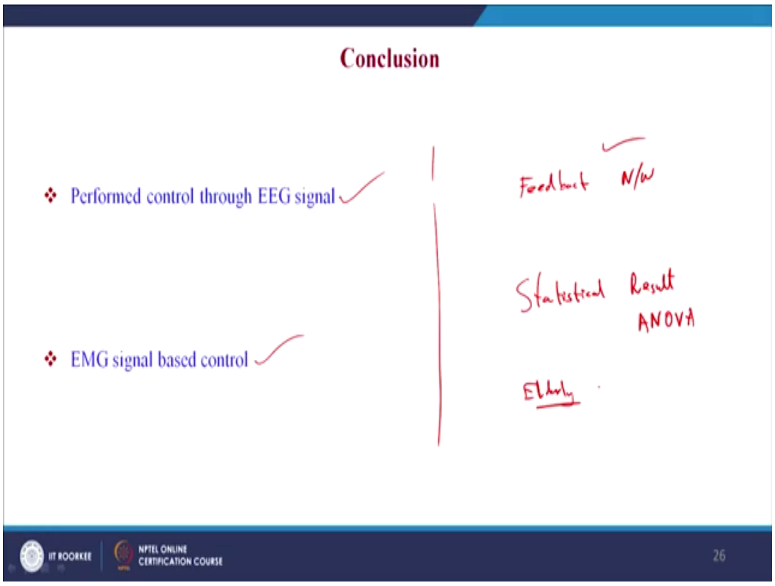

With this we finish this lecture by the conclusion; that we have developed yeah learning based muscle computer interface in order to control the exoskeleton. And, then we have performed the EEG based signal intension based control of the exoskeleton. So, that by this lecture we proved that we have developed first the EEG based EMG based control. That is the learning scheme that is based on surface electromyogram signal based approach and the second one being the control through brain signal that is electro encephalogram signal.

But what we have to do in the near future is, to have the performance of the system or the trained network with the feedback network and compute the or compare the performance of the system. So, basically we need to go for the feedback system and we also should do with many human subjects in order to get the statistical results based on strict analysis of variance. Based on ANOVA we are planning to do the experiments with several human subjects especially elderly subjects. So, as to get the performance of the trained rehabilitation paradigms, to show the performance is better than the existing rehabilitation paradigms.

Thank you with this we wind up this lecture.