Remote Sensing and GIS
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Lecture - 18
Hyperspectral Remote Sensing - III

Today we will continue hyperspectral remote sensing lecture. So in this lecture I will continue how we are processing this hyperspectral remote sensing data to derive a meaningful information, right.

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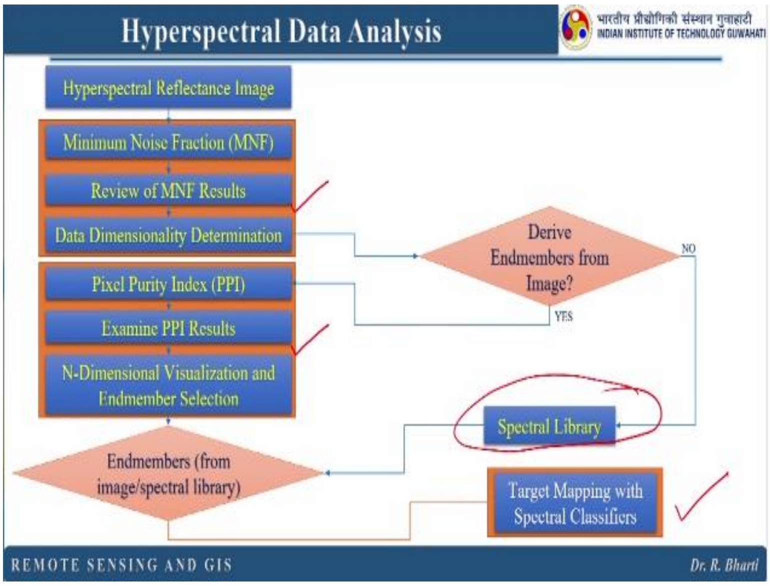

In this slide, I will bring the same flowchart, which I have shown you in my earlier lecture, how do we process this hyperspectral remote sensing data to derive a meaningful information. So here the first one is hyperspectral reflectance image. It can be hyperspectral emissivity image, but here I am intentionally putting this reflectance image because from the space bond satellite we are getting only reflectance image in hyperspectral remote sensing mode, right.

So hope you remember this hyperspectral remote sensing data is giving you the spectral response for each and every pixel, right. So in care if you are having this reflectance image and here I am talking about the Hyperion sensor, right, which is available in space. As of now, it is not in working condition, but you can download the archive data and you can try this processing.

So the next one is minimum noise fraction that means here the second step in this processing is to minimise the data or to derive the unique information. Why we are doing, because we are having contiguous hyperspectral data that means there will be many information which are coming repetitively, right. So we need to segregate those repetition and we need to derive the unique information from this hyperspectral remote sensing data.

So I hope you remember by PCA lecture, Principal Component Analysis. So this is the advanced version of principal component analysis which is known as Minimum Noise Fraction. I will discuss this in next slide. Now in the third state we have to review the MNF result and once we are done with reviewing then we can derive the inherent dimensionality of the data that means the unique information from this many number of narrow and continuous bands right.

After this processing, we consider we have unique values of reflectance for different materials in those images, right. Now here we need to derive the endmember, I hope you remember the endmember, endmembers are unique and pure spectra of any given material and object, right. I will discuss again this. In this particular flowchart here we have a criteria, right.

So in this criteria either you will use this image to derive the endmember or you can have the field investigation result, that means you have brought the spectroradiometer to the field, you have measured the reflectance spectra and then you want to incorporate those information and classify this image, right. So here in case if it is yes, you want to derive this endmember from image.

Then we have to run this Pixel Purity Index. Using that we can derive the endmembers from this image, right. We will discuss this detail, and then again we will examine this PPI result and we will plot everything in N-dimensional visualizer, so that we can perfectly identify this endmembers. If we do not apply this N dimensional visualization technique, then what can happen?

The selected endmembers can be of the regular or mixed pixel, right. In case if you do not want to go for this image endmembers, then what we can do, we have already selected or we have already generated the spectre library from this spectroradiometer. Once we have that then we can use this is spectral library to match with our image spectra, right. So here we have known spectral library where we know what is the object or material and what is their chemical composition.

So for them we have generated the spectral library. In this case we have unknown spectra which is derived from the image or which has been captured by our sensors, right. Now we need to analyse these two together, then only we can say the material is x, y or z. so that is why the last step is target mapping with spectral classifier, right. So here in this whole processing there are 3 major component.

First one is data dimensionality reduction, so that is here and the second one is how to derive this endmembers, either it has to be from image or from spectral library, right and the third component is how do we map this on field or on the image, right. So for that we need to use some classification technique that also we will discuss, because here the classification technique is different.

From the previous slide I have taken this data dimensionality reduction, here we have minimum noise fraction method and when we talk about pixel purity index, why we do that?

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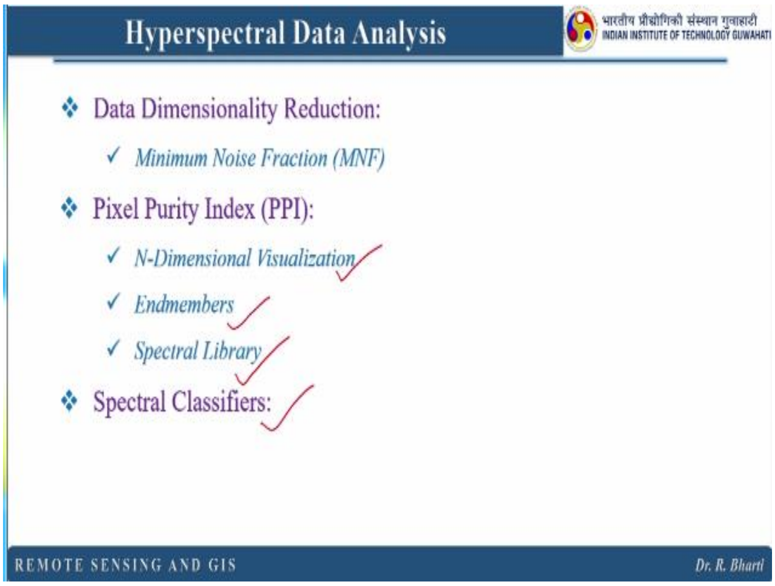

We do that to derive the endmembers, so here first we will visualise this N-dimensional space and then we will generate the spectral library, right. So spectral library can be from your image derived endmember or maybe from the field measure spectra. In both the cases we will have one known and unknown. So finally we will be using some classification technique and we will classify our hyperspectral image into several classes.

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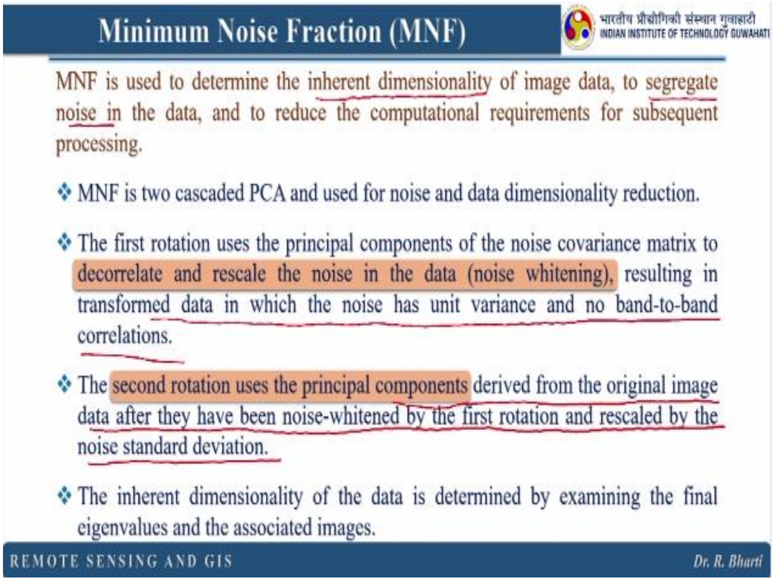

Let us start with MNF, so MNF is used to determine the inherent dimensionality of image data to segregate noise in the data and to reduce the computational requirement for subsequent processing, because if you remember that multispectral classification technique like minimum distance to mean, so we had only 4 bands. So the computation was very fast, it would not take even hardly 1 minute.

But here when we talk about hyperspectral data the bands are in 100s, like 200, 300, 400. So the computational time will be more. So how to minimise that, if we can derive or if we can identify what are the bands which are containing unique information and then we can remove rest, right. So MNF is one of the technique which determine the inherent dimensionality of image to segregate noise in the data and reduce the computational requirement for subsequent processing.

So here these 2 terms are very important, first one is to identify inherent dimensionality and second one is segregate noise from the data. So these two things we are going to perform when we are talking about MNF, minimum noise fraction. So MNF is 2 cascaded PCA and used for noise and data dimensionality reduction. The first rotation uses the principal components of the noise covariance matrix to decorrelate and rescale the noise in the data resulting in transform data in which the noise has unit variance and no band to band correlation, right.

In the second rotation it uses the principal component derived from original image data after they have noise-whitened by the first rotation and rescaled by the noise standard deviation. The inherent dimensionality of the data is determined by examining the final eigenvalue and the associated image. So here these 2 terms are very important. In the first step we are identifying the noise and we are decorrelating with the data.

So there will be no band to band correlation afterwards. In the second rotation we are going to identify PC 1, PC 2, PC 3 remember that from PCA, right.

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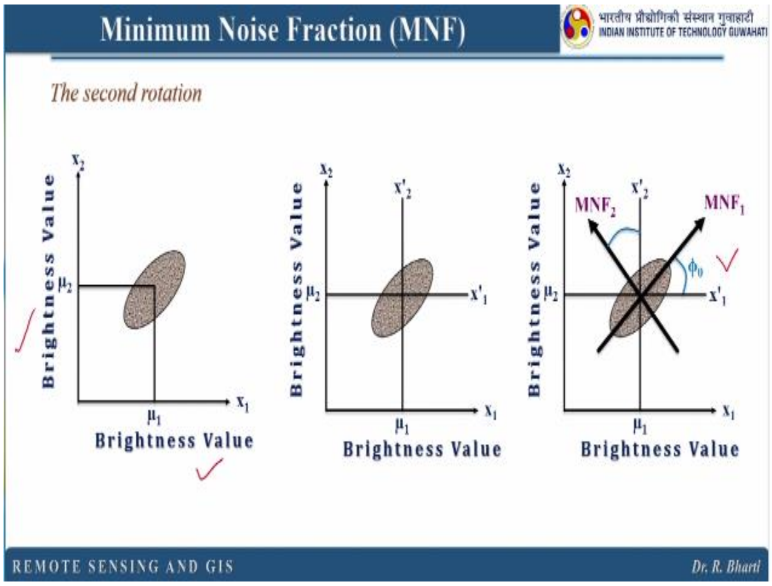

So in the second rotation it is as good as your PCA. So here you have 2 bands, band 1 and band 2, where you have high correlation, then you have rotated here with some angle and then your data will be uncorrelated.

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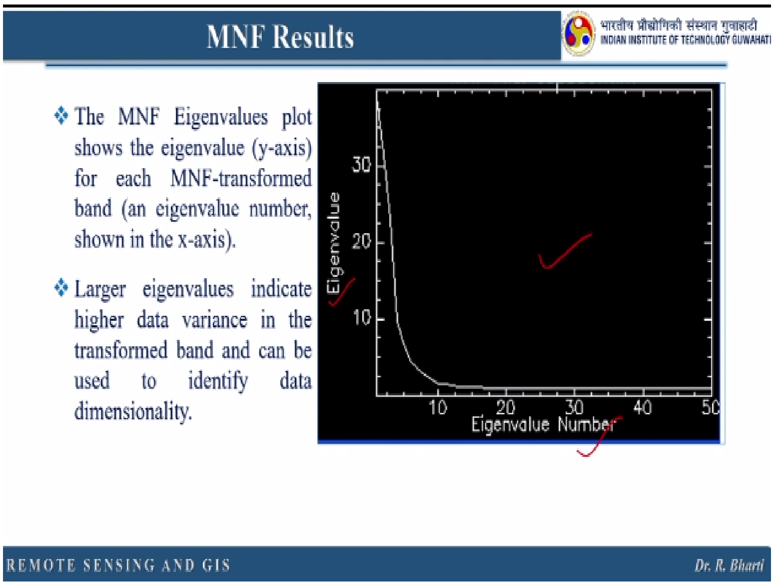

So there will be no band to band correlation between the data sets after MNF processing. So the MNF Eigen value plot shows the Eigen value for the MNF transformed band and here you can see. This is the eigenvalue number and this is eigenvalue and the larger eigenvalues indicate higher data variance in the transformed band and can be used to identify data dimensionality.

So this is one of the information based on that we can identify what is the inherent data dimensionality of the input image, right. So when I am talking about input image, that means I am talking about the all the bands, right. So in case of hyperspectral image it will also contain 200 or 300 bands right.

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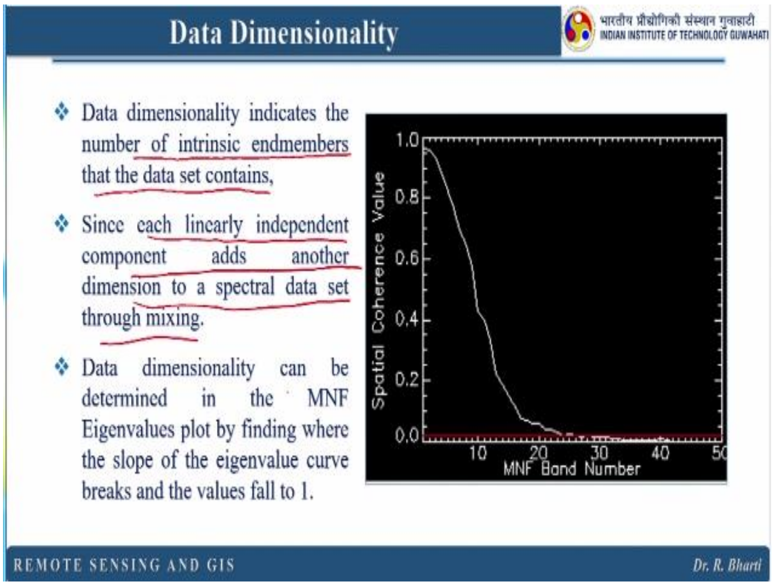

So here how do we exactly do this? So data dimensionality indicates the number of intrinsic endmembers that the data set contains, right. Since each linearly independent component adds another dimension to a spectral data set through mixing. The data dimensionality can be determined in the MNF eigenvalue plot by finding where the slope of the eigenvalue curve breaks and the value fall to 1.

So if you see here, it will be somewhere here, right. So here if you remove the bands which are coming below this line or you can come up with your own logic that if this is the spatial coherence value that means band to band correlation will be less. So you have to examine the corresponding image or the output image and with this value, right. So then you can come up with the final conclusion that this is the data set or this is the inherent data dimensionality of your hyperspectral image.

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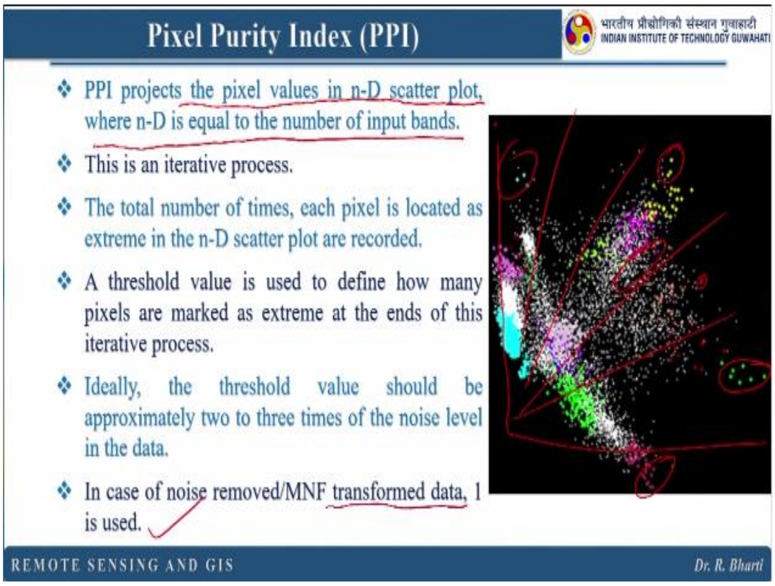

So once you have identified all the bands which are unique then we will run this pixel purity index for the endmember extraction. So PPI projects the pixel values in n-D scatter plot, why this is n-D scatter plot? Because here n-D respond to your number of input bands, right. So here if you are using 100s of band then 100 dimension scatter plot. So that means PPI projects the pixel value in 100 scatter plot where n-D is equal to the number of input bands, right.

This is an iterative process, so again it has to be modified or it has to be critically reviewed, so that you can find only the pixels which are coming in the extreme, that I will explain you. The total number of times each pixel is located as extreme in the n-dimensional scatter plot are recorded. So here what is happening, here you can assume there are n-dimension, right and these pixel values are changing why because we are rotating the axis.

So when you are changing the axis one by one what will happen this pixels, these are the pixel values right, does not matter in which colour they are. So they are the pixel value plotted in n- dimensional space and here you have to find out those pixels which are coming in extreme. So extremes means these are the extremes, right. Here you can control the speed as per your requirement.

And then you just keep a track of pixels which are coming in the extreme and what is happening when you are changing to this axis. So ultimately you have to find out those pixels which are coming frequently in the extreme, right. So our threshold value is used to define how many pixels are marked as extreme at the end of this iterative process, that is we are having flexibility.

Ideally the threshold value should be approximately 2 or 3 times of the noise level in the data. So remember when you are using MNF corrected image that means the noise values have been whitened and the values are 1. So in case of noise removed MNF transform data, 1 is used, right. So 2 or 3 times of the noise.

I have another image, where I can explain the extreme pixels have been marked as endmembers. So now here you can see this is one type of endmember, this is another type of endmember, this is third type of endmember right and these are coming in the stream, that is why I have marked them as endmembers. So as of now these are marked only to select in the image.

Now correspondingly we will have the spectral response of all these pixels. So remember when your marking hear, it may look like these are very few, but when you actually see them it may be hundreds of thousands of them here within this particular circle.

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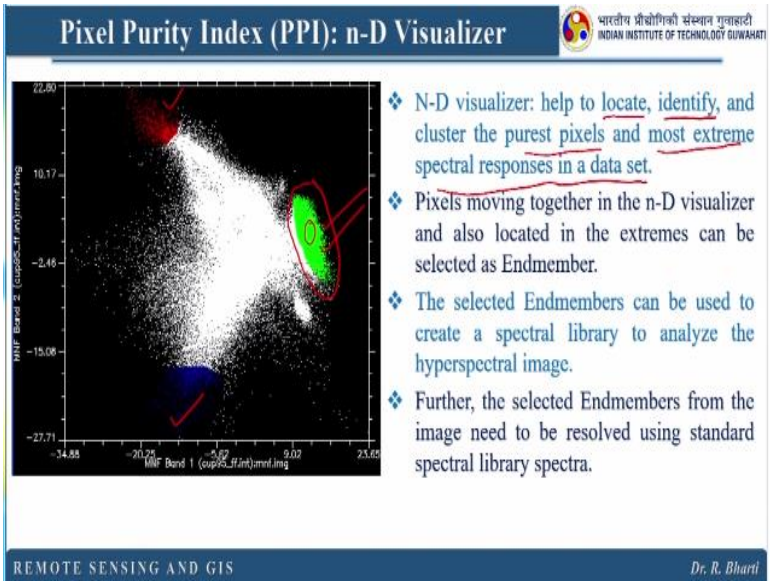

So in this n-D visualizer basically what we are doing? We are locating, we are identifying the clusters of purest pixel and the most extreme spectral response in a data set that means they are not co-related much with each other, right. Pixels moving together in this n-D visualizer also indicates that there are actually having same properties. So they can be grouped together. So that is why all these pixels are grouped together in one class.

The selected endmembers can be used to create a spectral library to analyse the hyperspectral image remember that spectral library of either collected in the field or derived from the image. So these are the pixels which will be used to generate the spectral library and we call it endmember extracted from the image and that we will use for the classification of this data.

So further the selected endmembers from the image need to be resolved using standard spectral library. So this is very important to understand.

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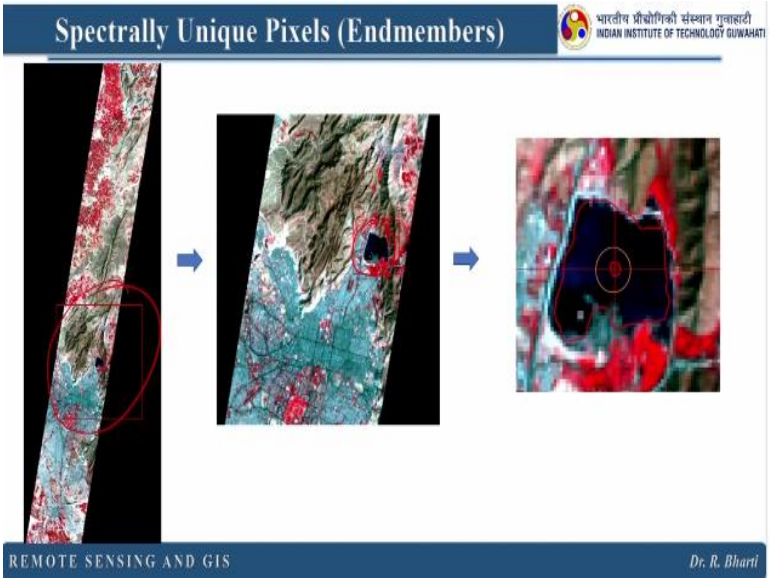

Let me explain you what exactly I am calling endmember, right. So here this is one image right and this is the zoomed of this particular portion right and here you can see this is a water body and this is further zoomed image of this water body. Now here what do you expect, so these corners may have some influence of soil and other materials, right, but when you see the centre pixel of this particular lake we expect that contains pure water.

I should use the purest pixel which contains only water, right, so then we will derive this and we will collect the spectra and we will say this is the end member of water derived from this image, right. Now whether it is possible to do for all the classes? No, because this spatial resolution of this particular data is 30 meter which is Hyperion. Now here in 30 meter do you expect only water will present? Yes, it is possible, but whether you expect that same soil type or rock type will be there in 30 by 30 metre? It is very difficult, right.

So though we know this we extract some of them and we say that this is the end member, I am going to use to classify this whole image based on this spectra, but still I do not know what is the chemical composition of this particular material which is derived from this 30 by 30 meter. So in that case what we have to do, we have to compare this image derived endmember with our spectral library generated from field investigation or maybe lab investigation, right.

So this is the spectra of vegetation and this is the spectra of vegetation from field and this is the spectra of vegetation from lab, right, so you see there may be slight difference between this and this, right. So you need to use these two any of them as a standard and then you will say this particular image derived endmember for vegetation is matching 10%, 20%, 30% with the spectral library derived from field or maybe from lab, right.

So after doing this what exactly we have, we have the matching score between these two, right, but still we do not know what is the chemical composition. So in field when we go for the spectral measurement, we also collect the sample for lab analysis. So once we have the sample with us in the lab we use the conventional techniques and we derive the chemical composition of that particular sample and then we know that this is the chemical composition and this is the corresponding spectra of this material.

And if it is matching with our image derived endmembers, that means the chemical composition of image derived endmember is as good as your sample, right. In that case we can deconvolve or we can resolve the chemical composition in terms of x y z, right. I hope you have understood this part.

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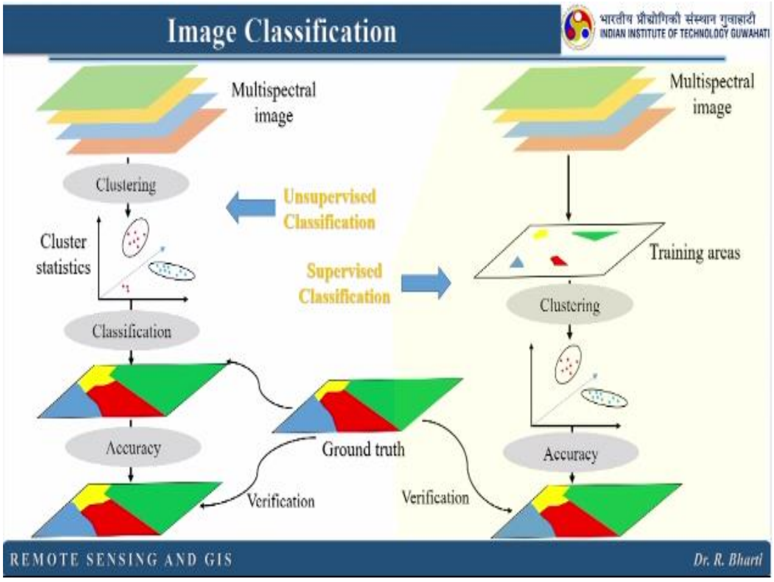

So once we have this endmembers and you have already characterized this using this spectral library. Now how do we perform this classification, because here the numbers are more for the spectral band. So we need to use some different kind of technique then only we will be able to classify our hyperspectral pixels into different classes, right.

So here I hope you remember in unsupervised classification what we used to do? We used to generate the clusters based on some physical laws. In case of supervised classification, we used to provide the information and based on that the algorithm will generate clusters and ultimately each pixel of the input image will be classified into those classes. So here in this hyperspectral remote sensing we will be working with supervised classification technique.

And we will provide our endmembers as a training data, right and once we do that then the algorithm can classify, but what kind of algorithm.

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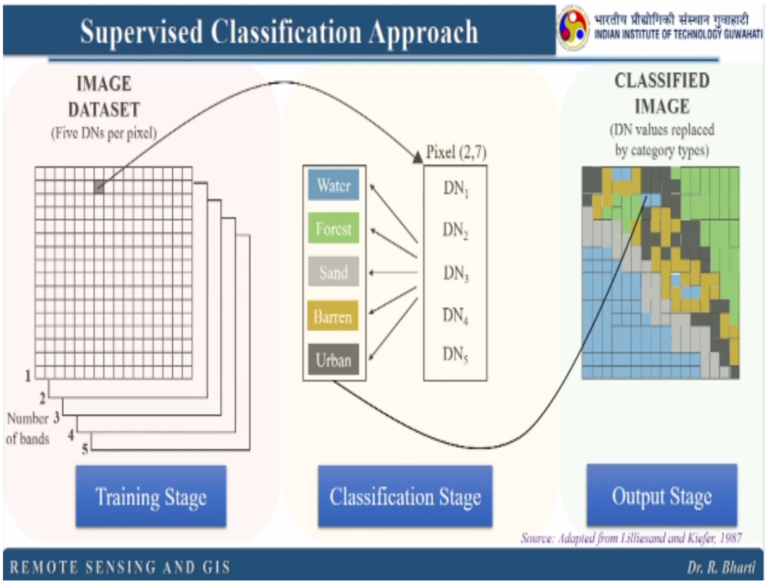

Or what are those algorithms which are used commonly here, that we will discuss. Now here I just wanted to highlight what is the complicacy when we use hyperspectral data. When you are having 4 or 5 band image, then you have only those 5 values for each pixel, right, but when we are having 100s or 200s or 300s band then for each pixel you are having 300 values, right, in different wavelength region. So how do we exactly perform this classification that is based on some spectral classifier.

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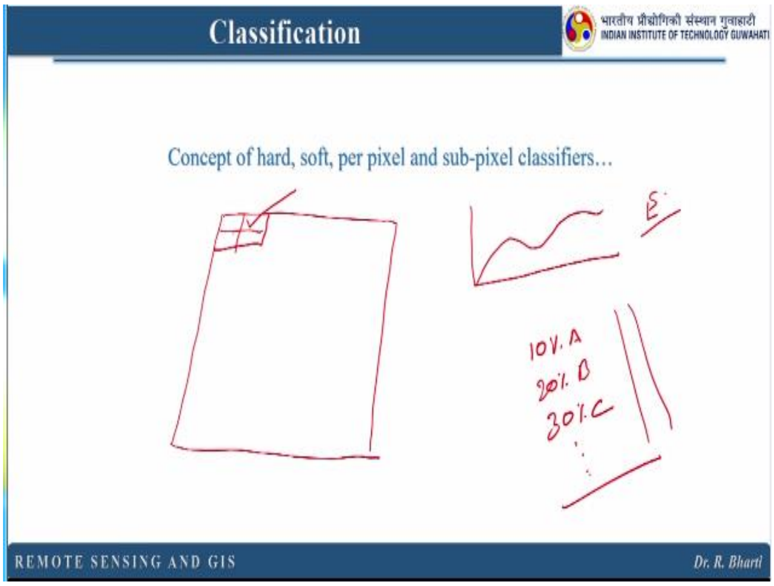

Now here I want to introduce few different terms like hard classifier, soft classifier, per pixel classified or sub-pixel classifier. So if you see the name itself hard and per pixel, right, so they are having same meaning, right. Now let us assume this is your image, does not matter whether it is a multispectral panchromatic for hyperspectral image. So here if I am talking about these 2 classification technique.

That means each pixel of this image will be classified into different categories and one pixel can have only one class, right. It cannot have 2 classes at a time. When we are talking about this soft classification or soft classifier or sub-pixel classifiers then we can have 2 or 3 different classes within this particular pixel, right. So how we are doing this? We are going to resolve the spectra which is derived from this image, that we are calling endmember into different chemical composition, right.

And based on that we will say this particular pixel is having 10% of A, 20% of B, 30% of C likewise. So here for each pixel we are having this information which we never had with multispectral data, that is the advantage when we are going for the hyperspectral remote sensing data, right. Now, I hope you are clear about it, this hard and per-pixels basically each pixel will be classified into only one class.

Whereas in soft classifier or sub-pixel classifier, you can have different classes within a pixel that is why they are called soft or sub-pixel classification techniques, right.

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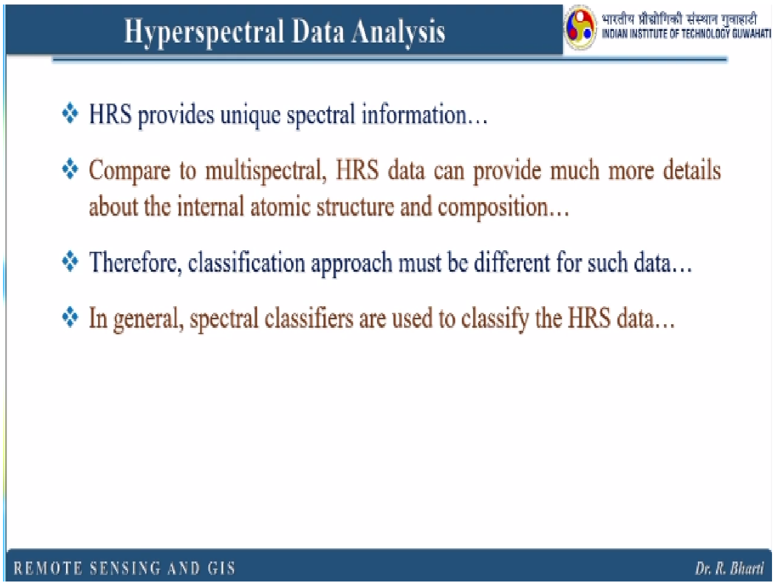

So in hyperspectral remote sensing data analysis basically we have certain advantages that I want to highlight. So hyperspectral remote sensing provides unique spectral information which we cannot have with multispectral and panchromatic data, compared to multispectral, hyperspectral data can provide much more detail about the internal atomic structure and composition, why because our bandwidth is less and number of bands are more and they are contiguous in nature, right.

Therefore, classification approach must be different for such dataset, when we having certain advantages there will be some complication, right. In general, spectral classifiers are used to classify the hyperspectral data.

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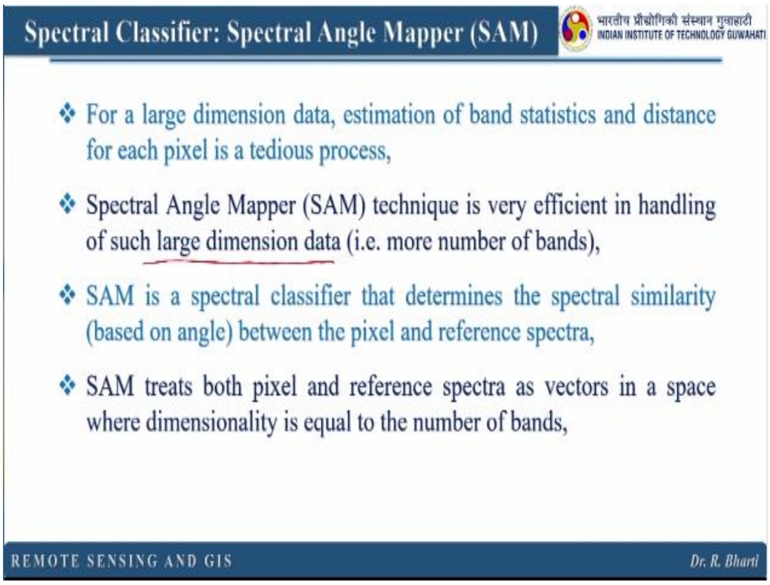

So one of them is Spectral Angle Mapper which is commonly known as SAM. This is one of the most popular classification technique. So for large dimension data estimation of band statistics and distance from each pixel is a tedious process, right, if you compare with minimum distance to mean or maximum likelihood it is actually going to be tedious. So that is why we have to move towards some advanced technique where we can minimise our computational time.

The spectral angle mapper technique is very efficient in handling of such large dimension data that is more number of bands, right. So here even we have applied the minimum noise fraction to remove or to identify the inherent dimensionality and we have removed let us say out of 300 input bands we have selected only 200 for our processing to derive the endmember and to classify this particular image.

But still 200 is not less, so that is why we are calling it large dimension data. SAM is a spectral classifier that determines the spectral similarity based on the angle between the pixel and the reference spectra, how? Let us understand in the next slide. SAM treat both pixel and reference spectra as vector in a space where dimensionality is equal to the number of bands. So how exactly we are doing this.

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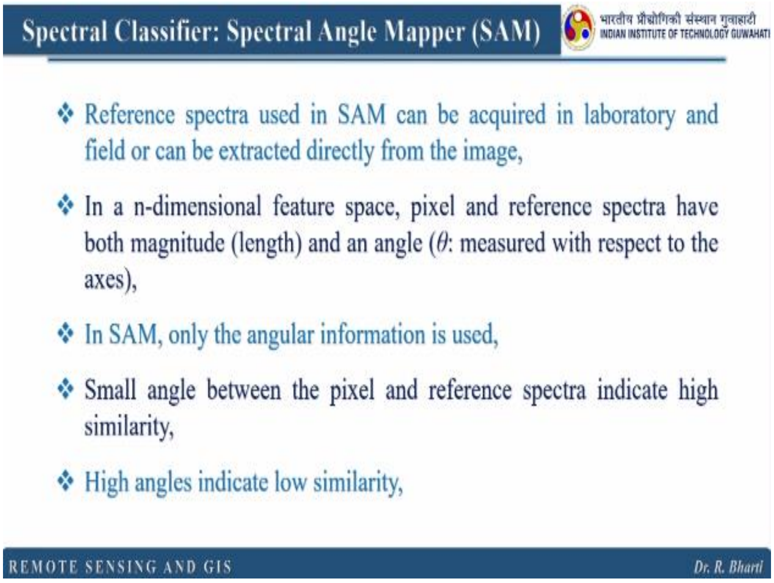

In SAM classification the reference spectra which we will be using that can be derived from laboratory or field or can be estimated or can be identified from the image. As I told you we need only endmember for the classification and that will be used as a training data. So here the training data or the reference spectra can be your image derived endmember or it can be measured in the field or it can be measured in the lab when you have brought the sample from the field to your lab for investigation, right.

So in a n-dimensional feature space, pixel and reference spectra have both magnitude and an angle that is theta and in SAM only the angular information is used. Remember here we are not bothered about their values, whether that is more or less we just have to identify what is the theta between the reference and the target. Target is basically your image endmembers which we want to classify.

So when we are talking about the target spectra, that means we are talking about the pixel, because we are going to assign a class to those pixels which have been identified for this classification. Now small angle between the pixel and references spectra indicate high similarity, right. So the high angle indicator low similarity, that means they are away from each other. If they are having very low angle that means they will have similar behaviour.

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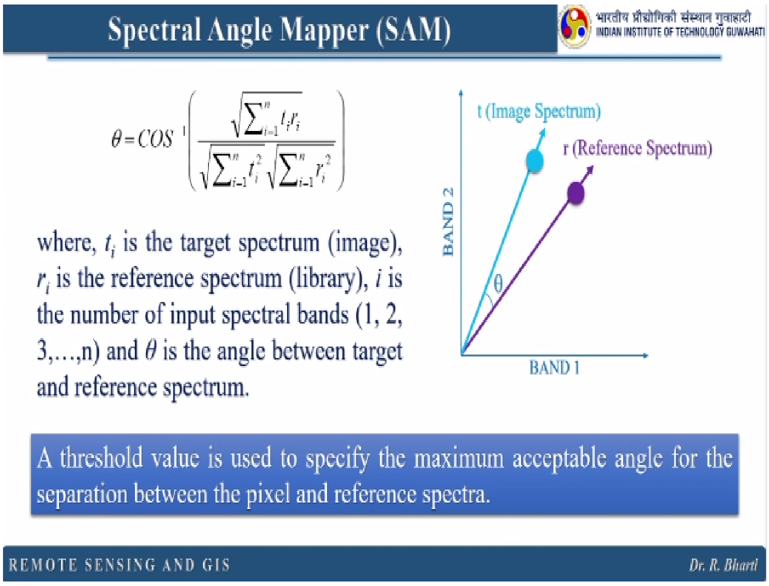

So here I want to just highlight if this is the image, right and just remember I am talking about this hyperspectral data, where this dimension is let us say 200 bands. Now when we want to classify our image the first pixel is considered and here in the first pixel we have derived the spectral response, right and this is the wavelength and this is reflectance and this particular data is used here as image spectrum.

Whereas this reference spectrum is endmember derived from MNF and PPI or maybe field investigation or maybe from lab investigation. So whatever you have done does not matter, here you need to have a reference spectra and that will be used to identify or to estimate the angle between target spectra and the references spectra. This is very important to note that if your image is in percentage reflectance.

So your values can be like 0-100 or if you have used some 10,000 multiplication factor right. So 10,000 multiplied with that value of that pixel that value will be completely different from this. So this particular position may change when you are changing the value in percentage or maybe if you are using multiplicative factor, right. So in that case this particular pixel location may come here right.

But this is not going to affect the position or the angle between these two, right. So in that case it is very safe to use spectral angle mapper, you do not have to bother or you do not have to convert percentage reflectance or you do not have to match the units of the your input data with your reference data, right. So here it is only going to measure this angle and that is going to matter here, right.

So we will be using this equation to estimate the theta. So here t_i and r_i is basically your target and references spectra. Where t_i is the target spectrum of the image, r is the reference spectrum, i is the number of input spectral band that can be 1, 2, 3, 4, 5 or maybe 100s or 200s or 300s and theta is the angle between target and reference spectra. I hope you have understood this part.

When we have such method we need to provide some threshold, then only this particular images spectra will be classified into this, right. Otherwise if the threshold value is not matching or if the theta is more than threshold value then the next endmember has to be plotted here right and then this will be measured with this or if it is not matching then third one, then here, like that you will have maybe 10 or 15 reference spectra or I will call it endmembers.

So with respect to that you will estimate this theta and once this theta value qualifies your threshold value then only that pixel will be assigned to that class, right, so that is why threshold value is used to specify the maximum acceptable angle for the separation between the pixel and the reference spectra.

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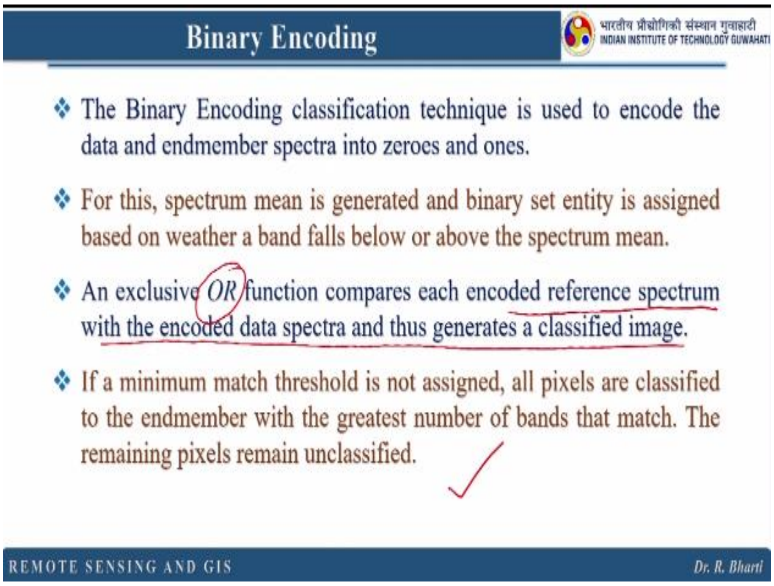

Now the next method is binary encoding. So the binary encoding classification technique is used to encode the data and endmember spectra into 0s and 1. For this spectral mean is generated and binary set entity is assigned based on whether a band falls below or above the spectrum mean, right, and exclusive or function. Remember this is or function compares with each encoded references spectrum with the encoded data spectra and thus generates a classified image, right.

If a minimum match threshold is not assigned, all pixels are classified to the endmember with the greatest number of band that matches. The remaining pixels remain unclassified. So that is going to happen when you are going to use this binary encoding method. The next method is spectral feature fitting. Most method used for analysis of hyperspectral data only indicate how similar the material is to another known material, right.

If you remember this spectral angle mapper or BE binary encoding, we are just going to compare whether they are matching or not whether how close they are with each other, right. So that is the theta value. So that is not going to solve our purpose because here we are talking about the spectral features. So direct identification of material can be done using extraction and matching of specific feature from field and laboratory spectra, right.

So spectral feature fitting is the first step towards a knowledge based system for more precise matching or identification of image spectra with the references spectra.

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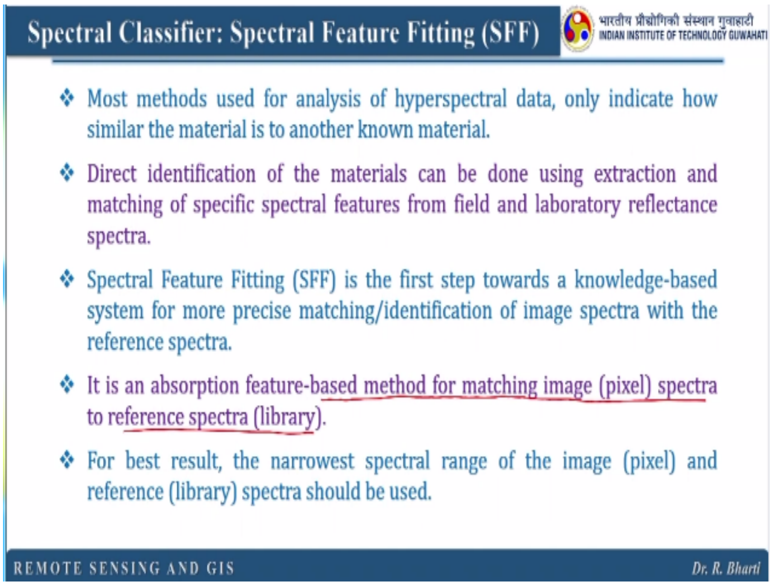

It is an absorption feature based method for matching image spectra to reference spectra, right, so image spectra is your basically target spectra and reference spectra is basically your library spectra which is derived from image as an endmember or from the field where you have used spectroradiometer or you might have brought that sample to lab and then you have measured the spectral response, right.

So for best results the narrowest spectral range of the image and reference spectra should be used. So what exactly I am trying to convey here, like for X material you have this kind of feature, right and this is the library spectra, so in the image basically the size of pixel is 30 by 30 meter, right. So you may have certain other objects here in this particular pixel. So you have 2 or 3 extra troughs right.

Absorption troughs, but actually I wanted to identify this material with in terms of X, whether it is 10%, 20% or 30%, in that case what we can do? We can use only these 2 absorption feature and the same wavelength range in your image spectra to match. Then we will not bother about this. So remember here when you are going to target X material then you should use all the absorption trough for the X.

You should not avoid any of them, otherwise, you will end up identifying some wrong material, right.

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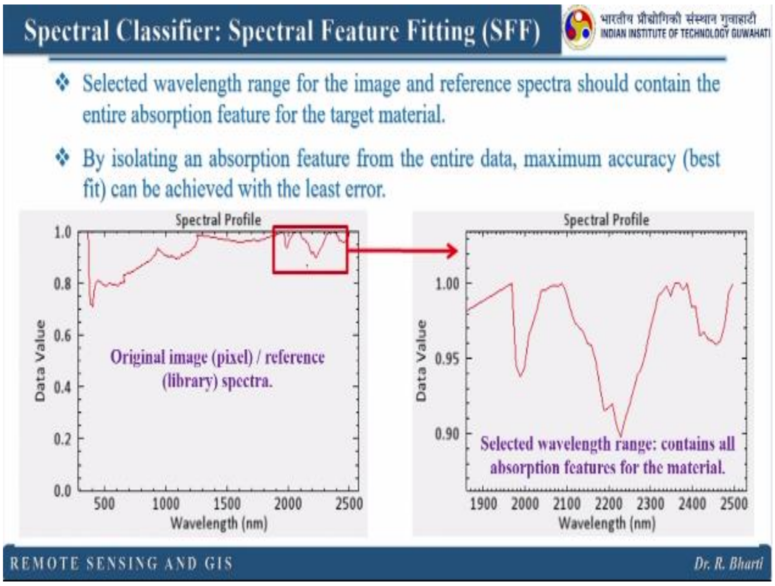

So selected wavelength range for the image and references spectra should contain the entire absorption feature of the target material, this is the same thing which I have explain by isolating an absorption feature from the entire data maximum accuracy or the best fit can be achieved with the least error.

So here if I want to study only this portion, why I have to keep all this thing because when I am keeping this we have to analyse and the algorithm will run for that also. So to segregate or to better identify we will just use this spectral range from the image as well as from the endmember or spectral library.

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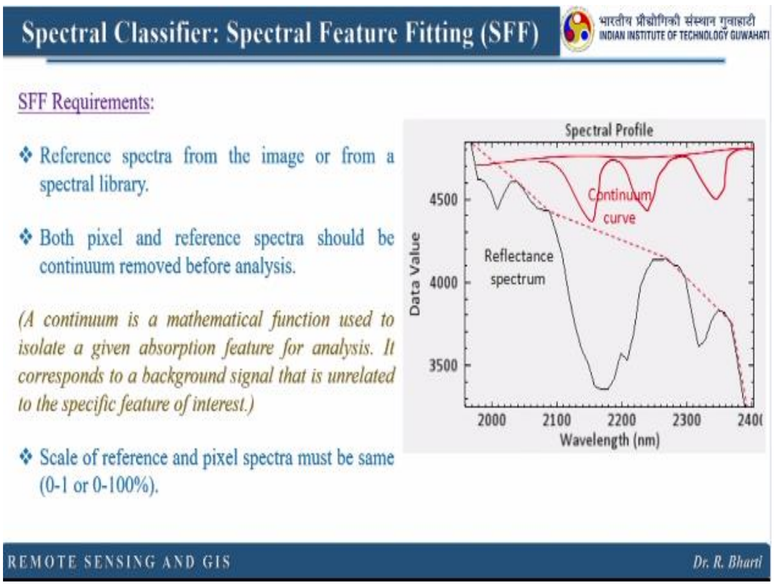

The requirements of SFF are listed here. Reference spectra from the image or from a spectral library. So this is the mandatory both pixel and reference spectra should be continuum removed before analysis, hope you remember that continuum removal. A continuum is a mathematical function used to isolate a given absorption feature for analysis. It corresponds to a background signal that is unrelated to a specific feature of interest.

Here this is one example where I am trying to fit a rubber band to all these peaks and the local maxima and then I will tighten this one, then everything will come to one line and from this we will be able to identify what is the depth of absorption for each wavelength, right. Scale of reference and pixel spectrum must be same, either it will be 0 to 1 or 0 to 100, right. It cannot be different as we discussed in SAM.

So in SAM there is no problem, if your reference and the target spectra are having different scale of the value, but here it has to be same.

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So what are the different steps, so it produces a scaled image for each endmember that you select. So here suppose you have provided 10 endmembers for this spectral feature fitting. So you will have 10 different outputs or the classified image and each image will corresponding to that particular endmember and based on the values you will be able to identify whether each pixel contains that endmember yes or no.

If yes, at what percentage, what is the best fitting, right. So subtract the continuum removed spectra from 1, thus inverting it and making the effect of continuum 0. It determines a single multiplicative scale factor that matches this reference spectrum to the pixel spectrum.

Assuming that an accurate absorption feature wavelength range, a large scale factor indicates a deep spectral feature right.

So performing a band by band or least square fit between each references spectrum and the pixel spectrum, it produces a root mean squared image for each reference spectrum, right. So here basically you will have a scaled image for each endmember and corresponding RMS image, right.

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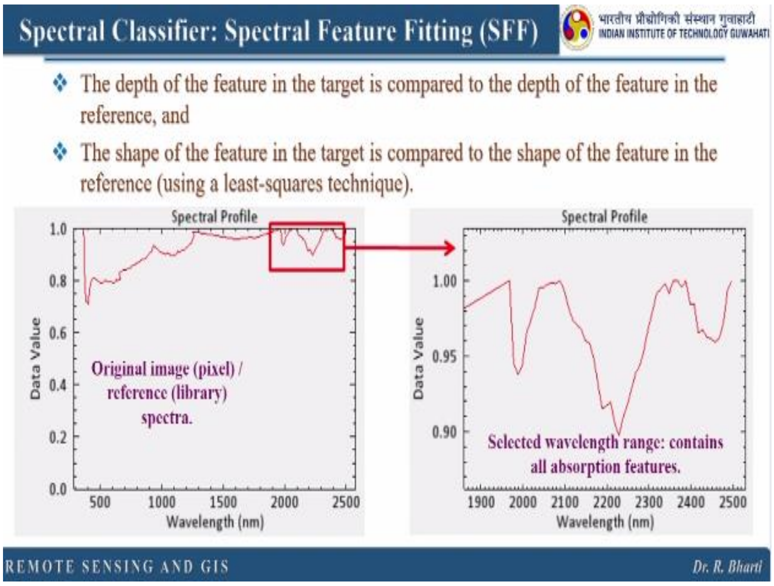

The depth of the feature in the target is compared to the depth of feature in the reference, right. The shape of the feature in the target is compared to the shape of the feature in the reference. So basically here we are going to compare 2 different things. We are going to compare the shape and the depth of absorption feature, for that we have remove the continuum.

So what is the shape, whether it is having 2 trough at different position, right, that is the shape and whether is it sharp or it is broad, right and then what is the depth of absorption so from the one, one line. So those 2 things will be compared in SFF.

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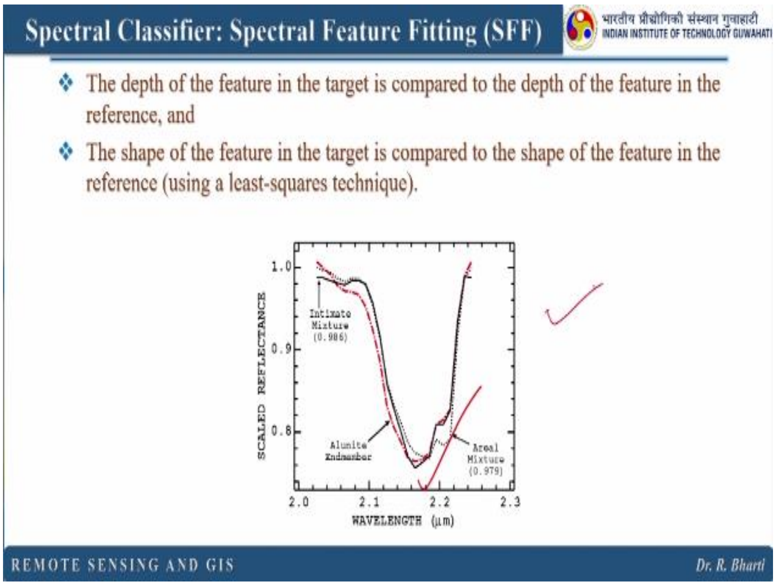

And finally you will be able to identify the endmember which corresponds or which is equal or which is similar to your image spectra. So in this case you can see this is the matching. So once you have such matching that means your image classification is perfect, right. You will have very less error in this classification.

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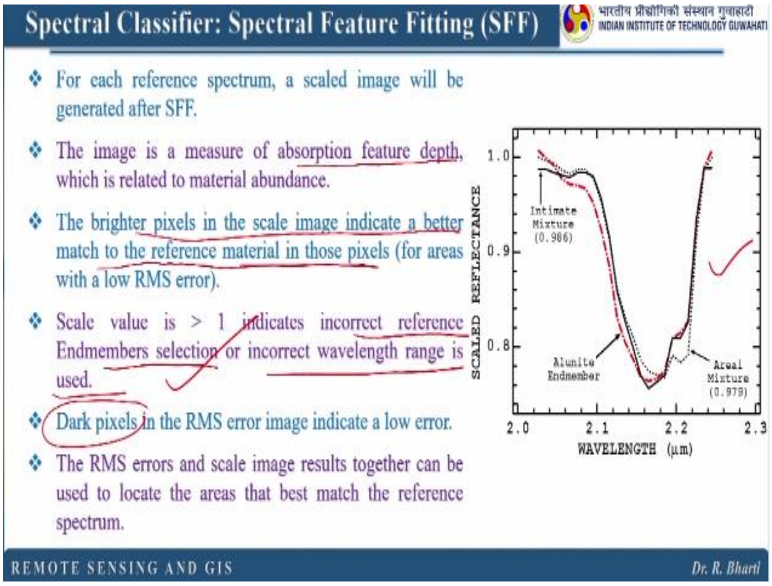

For each reference spectrum a scaled image will be generated after spectral feature fitting, the image is a measure of absorption feature depth which is related to material abundance. The brighter pixel in the scale image indicate a better match to the reference material in those pixels for the areas with a low RMSE error, that means the absorption feature if they are matching more, right.

That means you will have very good classification output and the intensity in the output image basically it indicates what is the presence of that particular material in that pixel. So that is why the brighter pixel in the scale image indicate a better match to the reference material in those pixels. So if matching is more you will have more higher value.

When the scale value is greater than 1, it indicates incorrect reference endmember selection or incorrect wavelength ranges used. So here if you are getting one value that means you cannot have one to one match or more than 100%, that means something is wrong. So you need to modify your endmembers and then again run this method.

Dark pixel in the RMSE error indicates a low error, that means again the dark pixel means less value of RMSE. So accordingly you have to see whether your classification is good or bad. The RMSE error and scale image results together can be used to locate the areas that best match the reference spectra for any given material, right.

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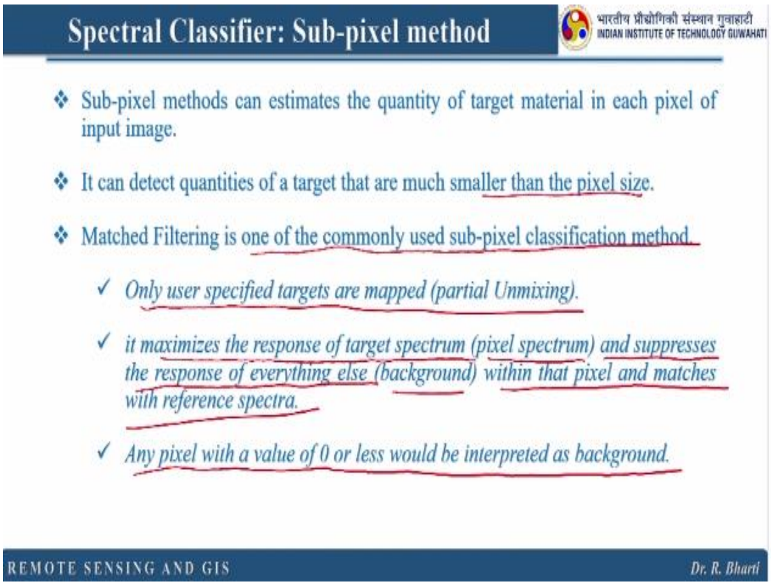

In sub-pixel method basically we estimate the quantity of target material in each pixel of the input image, right. It can detect quantities of a target that are much smaller than the pixel size. Matched filtering is one of the commonly used sub-pixel classification method. Here only user specified targets are mapped that is partial unmixing that means it is not going to resolve all the materials present in that image.

It maximizes the response of target spectrum that is basically pixel spectrum and supresses the response of everything else that is the background within that pixel and matches with references spectra. Any pixel with the value of 0 or less would be interpreted as background. So this is the limitation with this particular matching filtering.

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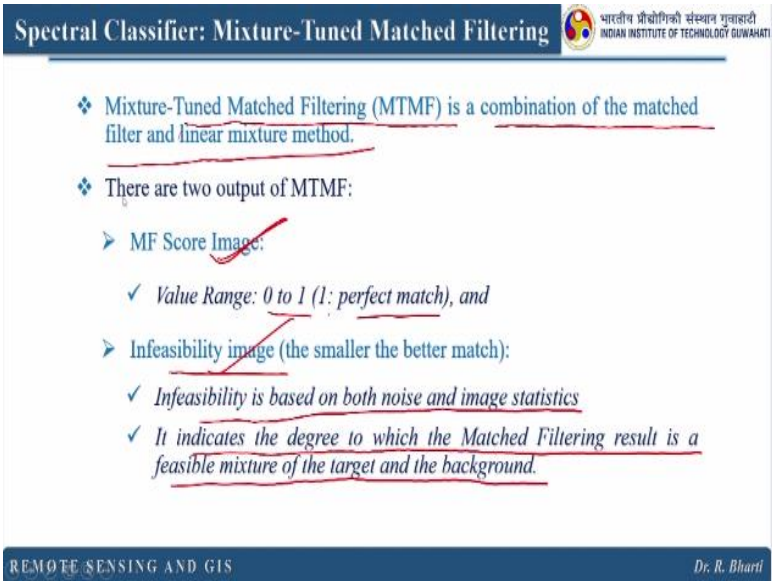

Now we have come up with mixed tune matching filtering. So in mixed tuned matching filtering method it is a combination of matched filter and linear mixing method, right. There are 2 outputs of MTMF, here the MTMF score and infeasibility report, that is in form of image. So the value ranges between 0 to 1 and once you are having 1 in scored image MF score image, that means it is perfect match.

So close to 1 or towards 1 that is good, infeasibility image, here it is based on both noise and images statistics and it indicates the degree of which the matched filtering result is a feasible mixture of the target and the background. So that is why here you need to be very careful when you are analysing this hyperspectral remote sensing data, because you are having more information.

And the processing is little bit complicated than your multispectral and once you are having more information then your responsibilities are more to be careful about the processing part. Today I will end my lecture here and we will continue this hyperspectral remote sensing in next lecture. Thank you.