Image Signal Processing
Professor. A. N. Rajagopalan
Department of Electrical Engineering
Indian Institute of Technology, Madras
Lecture No. 72
Applications of Restoration, and Image Deblurring Method

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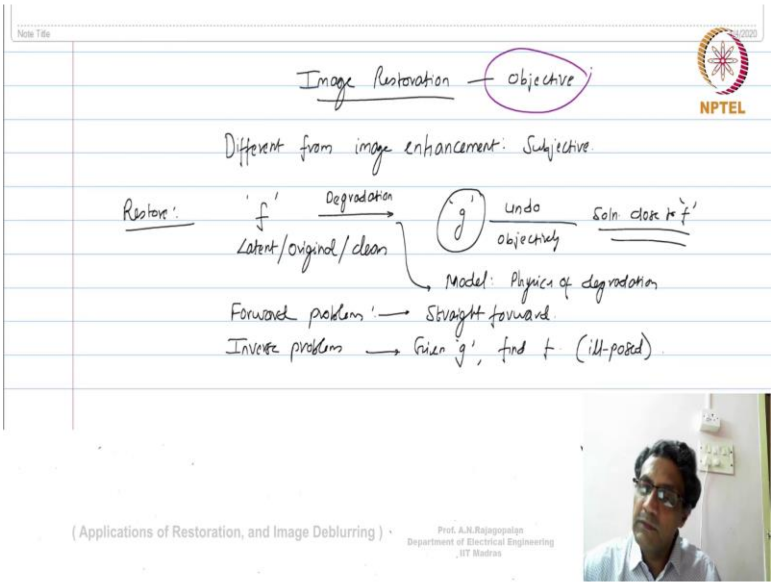

So, our next topic is Image Restoration, Image Restoration. The earlier topic that we saw was what was called Image Enhancement. Now, this is very different from image enhancement, different from image enhancement. As you would have noticed, image enhancement was more more subjective. There was lot of subjective issues that we had. So, it was more about enhancing contrast, illumination composition and so on.

Somehow, enhancing the visual appeal of an image. And as I said earlier, the visual appeal some people may like while now the same kind of visual appeal may not be, may not be uniformly applied across people. Restoration on the other hand is very objective, objective and when we say restore, what we really mean is, mow we would have liked to see an image f, but this is like the latent or the ideal image, latent, original, whatever you want to call it, clean. It goes by various names, clean image and so on.

What you end up seeing is something g. Instead of f, what you actually end up seeing is g and f has undergone some kind of degradation. Degradation does not kind of always mean only in Nosie or something, you could have various kinds of say, degradation, some of which are enlist. If undergoes some kind of degradation, it could also be a noise and the combination of other factors to give you g. And the idea is that what can you do in order to undo this kind of degradation and do objectively.

By objectively what we mean is, we know we have a degradation model that means we know the physics of degradation, we know the physics of degradation, and we would like to see, and we would like to see what we can do in order to undo this g, so as to be able to get a solution that is close to f, close to f. f is what we are seeking. Now, you may not be able to get f, which is always you may not always be able to get back at f. Therefore, typically, you would not actually get back at f, but you will get something that is close to f. So, we say, so we need, so we need a solution close to f.

Now, this process by which f gets converted through some degradation into g is called the forward problem. And then, and the process by which you take this observation g, which is actually a degraded observation, then you pass it through something, whatever, some kind of a processing that will undo this degradation in order to give you back your solution, the original image that is called the Inverse Problem.

Now, forward forward problems are typically well posed. I'll talk about what we mean by well posed. So, so this is kind of straightforward, so here all that you need is the image and then somebody gives you a degradation and then say, straight, use the physics of wave formation and then and then in order to be able to produce g. Now inverse problem is like given g, given g (estima) find f. So, therefore, this is like your observe, you have an observation and you need to find it out. This is typically an ill-posed problem. And we will see, we will see what it actually means.

This, and this notion of ill-posiness , ill-posiness is not something that is only limited to the, to actually restoration domain or the image processing domain, it is something that occurs straight across domains that does not have to be just an electrical that a problem or something it can occur in anything, in any domain. And therefore, most of the things that we will do will be kind of generic in nature. These are things that you could apply apply in various problems.

And therefore, you have a kind of kind of what you say what you say, what do you say a commonality, a commonality across these problems. And therefore, whatever solutions we have will also be kind of generic in nature. But then of course, we will focus on some of those image processing problems that are very interesting to solve within this kind of restoration framework.

So, the key thing that separates it from enhancement is this notion of objectivity. So, its more, its more firmly firmly say grounded. This is that we know exactly what we are asking because we kind of believe that we understand what is a forward forward process, what is the degradation process. And we try to see if we can undo undo that process, that that really is the goal as to see, the goal of the restoration. Now there are various (applica) I mean, so, this kind of restoration task, which is like solving an inverse problem has applications in various areas within image processing itself.

For example, we have all seen, see, for example, we have seen image blurring. This is like a forward problem. Somebody gives you an original image, you just clean and then says this is a point spread function with which you should blur it, and then say as you add some noise to it, you get your g. So, when you have these g is equal to h of plus n, that is like a forward problem. So, we know how to actually do that. We have done it. We have done it for the space (inva) space, for the space variant case also. Now that is a forward problem.

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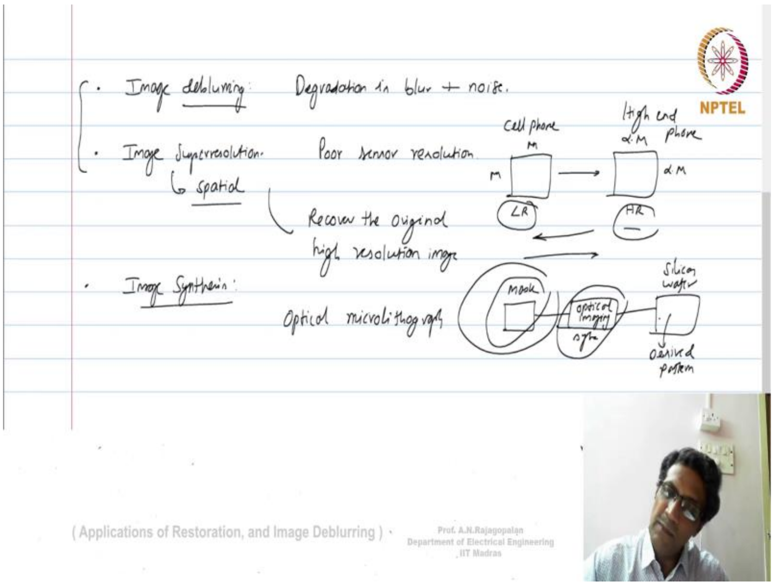

The inverse problem is what is called image deblurring. So, in image deblurring, we just give you a blurred observation. And we will ask what was the, what is the, can you say, restore re-original focused image. So again, that they, though they have the knowledge of the point spread function or not, and how much knowledge you have of noise and all that, we will have to see, how we can incorporate within this framework. So again, so, to repeat, I mean, deblurring is something that we have not looked at yet. The forward problem of image blurring we have seen, but then deblurring we have not seen.

So, so deblurring is like given a blurred image estimate the focused image. The see, then there is something called Image Super Resolution, Image Super Resolution. All these, so, in this case, when you talk about the degradation, the degradation in this case is blur. When you talk about the image deblurring, so the original degradation is blurred, and probably noise, is blur plus probably some noise, which can be AWGN typically. Image super resolution here, this is because of the, because of poor sensor resolution. So, degradation in this case is really a sensor resolution.

And when we say super resolution, we really mean spatial super resolution. There is also something called Temporal Super Resolution, and so on. But then we limit ourselves to now spatial super resolution. So, it is like saying that, I give you an image, which is of a low quality, that means we have let us say, M cross M pixels. And then I want you to produce something, which is like alpha times M, alpha times M, where lets say, alpha could be like 2 3, whatever, you want to go up by a factor. So, that is like saying that I have a low-resolution sensor here, let us call this LR.

And then I want to take this image and be able to produce a high resolution made out of it. This is again an impose problem because it is easy to get given a high resolution, getting the low-resolution image is straightforward. But then given a low-resolution image, when you try to solve the inverse problem to acquire high (reso) to sort of produce or estimate a high resolution, made, that is an impulse problem.

Remember, this is not the same as interpolating image, because interpolation image does not introduce anything new, whereas super resolution is supposed to recover the original image. So here, you are supposed to recover the original, original high-resolution image, which, of course, you are not able to see the original original high-resolution image. You are not able to see this image, of course. All that you can see is this low-resolution version of that, which we call as LR.

So, you can think of this as a cell phone kind of, a poor cell phone, and this could be a high-end cell phone. So what you are sort of saying is that, what you are sort of saying is that I can, I will, I would like to capture because if it is a cheap cell phone, it cost me less therefore, I will actually produce, I will capture a low quality image, but then I use some signal processing algorithm, which will then, then tell me which will then kind of give me the equivalent of what I would have otherwise capital with a high-end phone.

So, you take this LR, it will produce an HR as though, the HR was captured from a high-resolution phone, the sense that it saves me a lot of money. So, so the idea is that these are 2 problems that we will definitely be looking at in more detail. And then again, there are there are several things that come out of this kind of restoration umbrella, these are not the only 2 problems. Sometimes, people talk about image dehazing, image, well before going there, let me also talk about what is called image synthesis problem, which is again closely related to a deblurring problem.

So, image synthesis, what is, so one of the areas where image synthesis is very important, because what is also called Optical Micro Lithography, it is called optical micro lithography. And here the idea is that, I guess that, I mean, the idea is that you want to be able to estimate a mask. So, let us say that this is a mask, this is an optical mask that you want to be able to estimate, that you want to find out what should be the (())(09:32). Again, iti s an inverse problem, there is an optical mask that you would like to estimate such that, such that when it when it goes through an optical imaging system, so optical imaging system, it goes through an optical imaging system in order to be able to say, in order to be able to produce, produce some kind of a print on a on a silicon wafer, so want to produce a pattern on a wafer.

So, here is a silicon wafer, and you want to find out what should be the mask such that when it is passed through a imaging system it produces a desired, so this is a desired, this is a desired pattern on the mask, sorry the desired pattern on the wafer. Now, you know exactly what you want in this case, which will be a desired pattern, but the thing is you would not know what is the mask, we should be able, which I should be solving for in order that when it is passed through an optical imaging system whose characteristics I might know, I would, I would see this kind of, this kind of a desired pattern.

Then, so, in the sense, this is called the synthesis problem. We are trying to synthesize a mask, an optical mask such static it gives me a certain output, a desired output.

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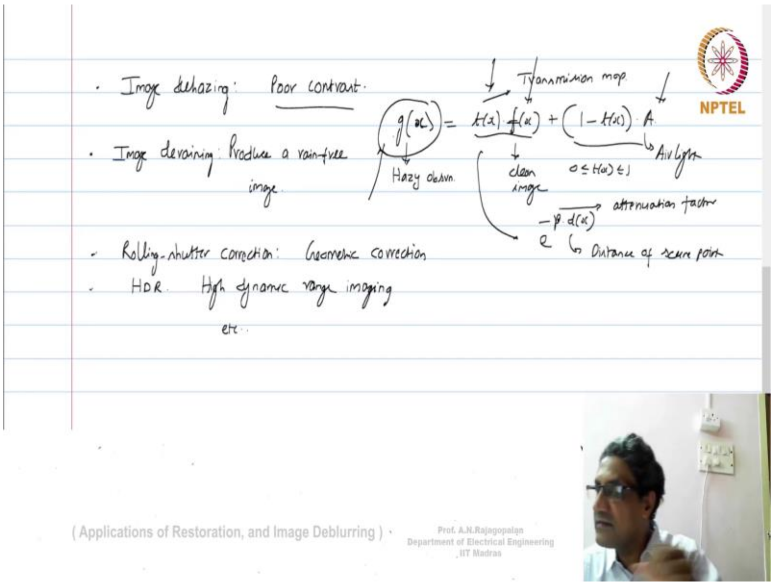

Now, furthermore, you can go on and then you can talk about even, let us say, image, something like image dehazing. Now, you know, we know that, we know that haze will lead, haze typically leads to a poor contrast in the metric whenever you see a picture that is affected by fog, haze and so on, you know that, that is such a, that is a pictures, looks actually very hazy, so in the sense that, they seem to have lost contrast.

And therefore, the idea is that dehazing would of course that will be able to remove the contrast and be able to give you back the original image. Now, if you look at the contrast switching problems that we saw earlier, which was using histogram and all, that was more and more the image enhancement kind of idea. Now here, this is more objective in the sense that we again, in this case we use the physics of, physics of image formation, in the sense that you might say that you might have observed a g of x comes as some let us say some t of x into let us say i of, we cannot show i of, lets, here we say f of x plus let me say 1 minus t of x into into A.

Now, this is the model, this is the model for haze. Now f of x is your clean image, which is what is what you would have liked to see, this is your clean image, which you would like to see. Unfortunately, you do not see f, you would rather, what you end up seeing is this hazy image, is a hazy observation. So, and then t of x is called is called really a transmission map, this is called a transmission map in the sense that this is this is typically given a e raised to minus beta times d of x, where beta is, beta kind of kind of represents attenuation attenuation attenuation, this is an attenuation factor.

This would also be a function of the wavelength, if it is underwater, it can be a function wavelength and so on. d of x is really the distance of the scene point from camera, of the scene point, and A is called the air light, so air light. So, the idea is that ideally you would have liked to see f, but then what you see is really kind of a convex sort of a combination of these two terms. This kind of a convex combination leads you to a minute to an image that looks hazy.

And the idea is that can you solve for the transmission map? What have I write? I mean, so the, so what is known to you is only g of x, and you are asking, “What is then what is then the original clean image?” That is like saying that how would the scene look like if it was captured on a day when there was no haze. So therefore, rate of f of x is like really a clean image that you would have otherwise seen, but then, you are not able to see that. So, when you go, when somebody gives you f, somebody gives you t, somebody gives you air light, you solve for g that is the forward problem.

Now, when somebody gives you g and says solve for f that is the inverse problem. So, dehazing is again is a inverse problem. Similarly, people have done what is called image deraining. Again, this is another kind of problem, where let us say I have a picture that is actually affected by rain drops, so I take a camera outside when it is raining and then I capture a picture. And the point is, because of the rain drops, I see an image which is affected by rain droplets and therefore, I would like to ask, “Can you sort of give me back an image such that it does rain free?” So, basically produce a rain free image. So here, degradation is really the rain.

And that produce a rain free image. And therefore, you would like to undo its effect in order to be able to produce a rain free image. And this this kind of rain will go on. I mean, and then there is something called Rolling Shutter Correction, which I mentioned to you right in the beginning. A rolling shutter is again an effect of motion of the camera. I mean, especially when you have, I mean, when you have a shutter mechanism that is rolling shutter, rolling shutter, which is kind of a correction that you need to do in order to account for the camera motion effects and this kind of a geometry correction.

So here, what kind of correction what we want to do, so, this kind of a degradation is really a geometry degradation, which we would like to do a correction for. So, this is thus a geometry correction. Then, I can also tell you, maybe some more, what is that, well I told you about super resolution, (())(15:02). And then so on, rolling shutter, and then you can high dynamic range imaging and so on, there are so many of them, it is called high dynamic range imaging and so on, etcetera.

In fact, I just wanted to mention that this deblurring thing that I mentioned in the earlier slide, deblurring, this has been, this is still used very heavily by the by the by the astronomical, astronomic imaging force, folks, (astronomic) astronomical imaging. This is used very heavily. And of course, it is something that we would also like to have in our own cameras, and so on. So, deblurring could also be an optical blur, motion blur and so on. Therefore, deblurring is again something that is very-very relevant even as I speak, even with respect to your own cell phones and so on. By the way, this 0, this tx is 0 less than or equal to tx, less than or equal to 1.

Now, with that, with that said, I mean, let me just show you a few examples of these. So that, so you get an idea about what I am actually would be trying to do really. Now, let me just pull this up, restoration. Now, before restoration, let me talk about the synthesis problem, which I share, which I say this for also an optical microlithography. If I show you that, then else, then we will see this. Image synthesis, let me first show you that.

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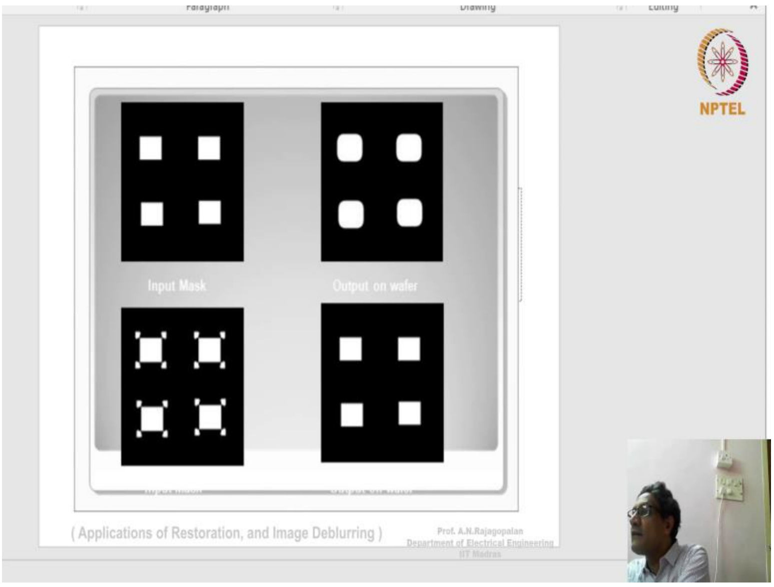

So, if you see here, I mean, if you see this image, what you really find is, what you actually find find find is that you would like to, so the whole idea is to be able to see produce, is to be able to see produce a mask such that such that the output looks sharp, and such that the binary wafer, whichever was the binary pattern, recipient of the wafer was actually sharp. Now, if you see this example, if you try to take a mask that is already sharp, the idea is that the binary pattern should emerge like this on the wafer.

But then if you think that the original mask should also be of the same shape as your final output, then what happens is when it goes through the optical process, all these all these all these these corners become rounded, which means that the binary pattern that you end up seeing right is not sharp like the one that is in the mask?" Then if you solve this problem, it is an inverse problem, it turns out that the mask ought to be like this, which is not at all easy to sort of imagine.

Remember, if you were to just sit back and think about what might be that mask that would lead to lead to a pattern that is really sharp at the corners, you will die. Just like that, if you were to sit back and think about what might be the mask, you would never have been able arrive at this answer. I mean, it looks like looks like you need a small little flower pattern at all the corners. This is not something that we can, that we can automatically do.

So, in that sense, I wanted you to clearly understand that at restoration is a more objective way, it is not about this visual appeal or something, this is about understanding what is a forward process and therefore, if that is causing some kind of degradation, then you want to be able to see inverted or in do it. So, so, in this case, in this case, the main synthesis problem turns out that the mass should be like this in order for the binary pattern should be, to be sharp with the corners. It is the synthesis problem that I mentioned. Then, as I said that there are also other problems within restoration, so here are some examples that I am sure you will like.

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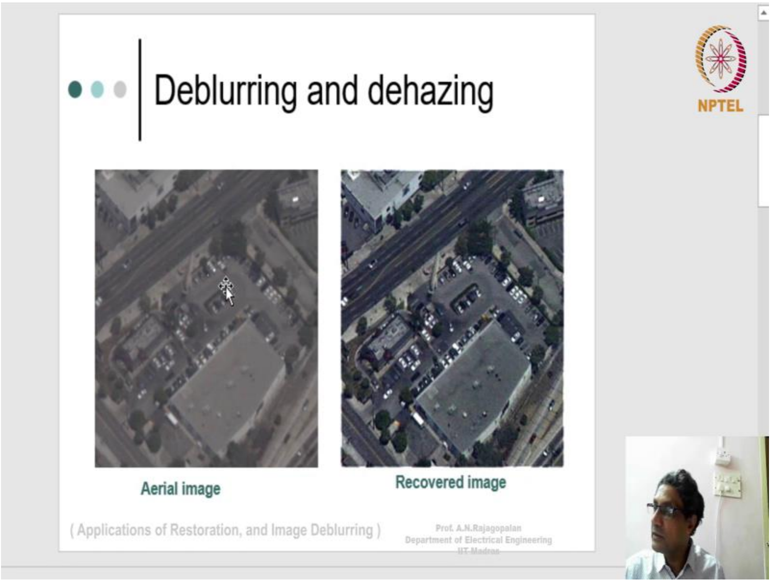

So, the first example let me show is about the dehazing and deblurring. So, for example, some of these factors that could also occur together, it does not have to be this dehazing alone or deblurring alone. So, in this case, you see an aerial image, so it is affected by haze as well as blur. Therefore, when you actually solve it as a kind of a restoration problem, the deblurring and dehazing problem, what you find is this, so in this, we clearly can see that it is a kind of haze free and it is also more sharp because we would, we are also be able to solve or remove the blur. Which is of course, in this case, we have made up a motion blur.

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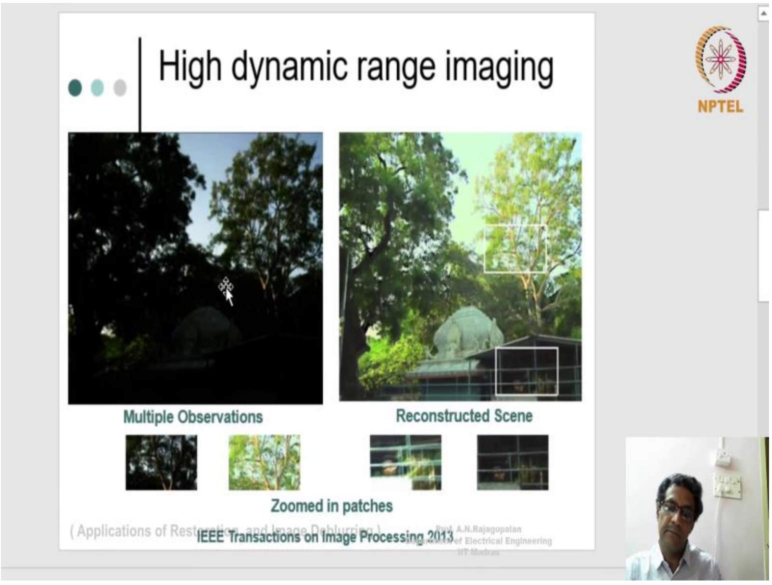

Now, moving on, you can also have high dynamic range imaging.

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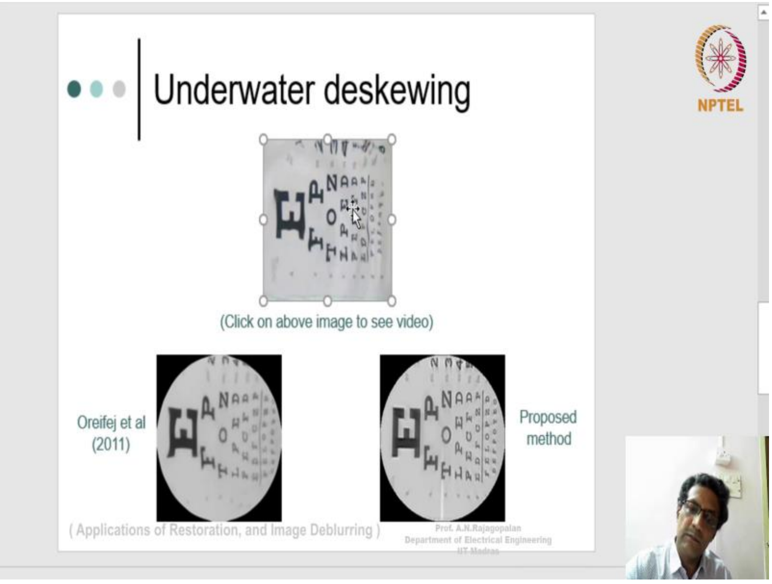

And then here is the underwater kind of deskewing. So, whatever I said till now, whereas, where all for surface images. Now, you can also see that if you, now let me just play this video. And so, it is like this. So, if I have, if I have, if I drop, if I drop a stone in water, what you would see is this, what you would see as a pattern is this. Let me just play that video for you. So, if you play this video, you will be able to see that, you will be able to see this water, this was a drop, drop of water. So, this is an image taken inside an aquarium, and we dropped, and then at the bottom we kept an eye chart. And you can see that all these all these letters and all becomes skewed.

And we would like to see the image without any skew. This is again a restoration problem. And if you solve for it, if you, without accounting for it, you would not be able to get kind of a good picture that is if you actually account for it, then all these letters and all get straightened up. But if you see here, they are all skewed. This is called the deskewing problem and so on. And therefore, the idea is that there, the idea is that there are so many of these problems, that you, that come under a restoration.

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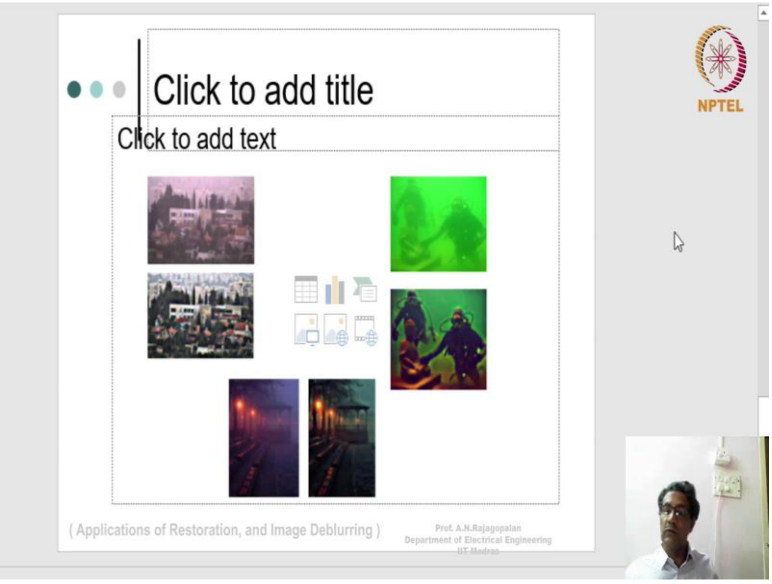

Here is another, this is about another kind of dehazing. So, here you have a hazy image and the near area by dehazed image. Now, if you will see here, this is an underwater image. So, till, so the early underwater, the test showed you was for deskewing, this for actually doing doing really what is called, what is called a colour correction. A colour correction in the sense that if you see this image is, this is an underwater image, therefore it has a lot of greenish tinge, simply because underwater, in underwater, the red wavelength is the one that gets activated the most.

The green and blue kind of survive and therefore, you see a big greenish tinge in this image that is you would have, so the idea is that you would like to do do colour correction. Such that you can actually retrieve these components, you like to retrieve the RBG (compo) the RGB components as you would have seen. Otherwise, on the surface, so if you solve a such a colour correction, and then you can actually find this image out.

Again, this comes under restoration framework. So, so so you understand what kind of a degradation occurs in the forward process, what these transmission coefficients are, how they can depend on the wavelength. So, that equation that I wrote for haze was a beta, which is said is an attenuation coefficient. So, in this case, an underwater beta becomes a function of wavelength. And therefore, we need to use that fact in order to be able to solve for the, solve for original scene image.

So, so I hope so I hope you get an idea about deblurring and all of that and then deblurring and deraining. And then, of course, I could not show you deraining example. But I have shown you examples of dehazing, high dynamic range and deskewing and so on.

So, moving on, we would like to, we would like to focus, we would like to focus our efforts on these 2 problems. We would like to look at image deblurring in particular, and then follow it up with some ideas about how to do image super resolution. And the idea is that if you can understand these 2 problems, then all that would change as you hope from one problem to another is the kind of observation model that you have, but then most of the idea, otherwise the general mathematics and all that follows is going to be somewhat similar.

I mean, I am not saying they are all identical and so on, but a lot of ideas that we talked about in terms of optimization, in terms of uniqueness, existence and conditioners, all those things will come up in a sort of uniform way across these problems. And therefore, even if you understand 1 or 2 problems well, it is enough. One does not have to kind of go through each one of these individually in order to understand understand the framework as such.

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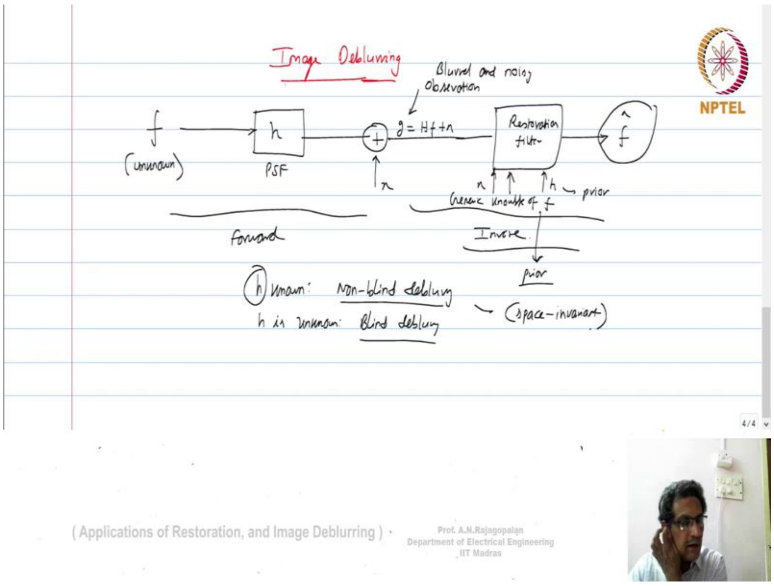

What do we mean by image deblurring? And I am going to show that in those problems are not easy to kind of deal with. The forward problem, like I said, is easy. If I give you an image and then asked you to blur it, you cannot blur it, that is a hard problem that is straightforward. But maybe deblurring is typically not straightforward. Even if you assume the simplest of situation such as a AWGN noise, space invariant blur, blurring known, all that, even then this turns out to be a hard problem to solve.

But then along the way, we will see how we can actually handle these, kinds of these kind of a difficult issue. The way you kind of model, as we all know, what do we say? We say that f is the original image, this is unknown, this not something that we can see, this is the unknown, this is what we want to solve for. What happens, it goes through an edge which could be a PSF point spread function, and then something gets added to this, let us say that I have got noise that gets added to this and then you get your g.

So, g is lets Hg plus n, where this h contains the impulse responses, its entries, zeros, impulse response rate impulse response entries. And what you want is really, so what you what you know is only g, we do not see f. And maybe, we might know h. And in some cases, we may not even know h. The problem is; given this observation this is really a blurred observation, blurred, so in this case it is blurred and noisy, blurred and noisy observations. So, the idea is that given this guy, what kind of processing will you do, what kind of processing?

Let us say, let us called this restoration, it is called as a filter, a restoration filter, what kind of restoration filter we will apply on g in order to be able to get back f? I would not say you will get f back, we will write f hat. So, that so that we understand that f hat is something that is something that is going to be close to f hopefully. Now, this is a deblurring framework. This is the forward problem, this is the inverse problem, this forward and this is the inverse. We would like to solve this problem.

Now, the whole idea behind restoration is that we like to know how much of the model we know. In most cases, we know the physics of physics of the image formation, what does lead to this degradation and so on. Therefore, in this case, this you will, might know, whether it is phase mere in blur or space very in blur. Accordingly, we would know whether to use the space invariant h or space variant h and so on. Similarly, noise, we may know that it is additive and then it could be AWGN, a Gaussian kind of noise. All these are things that we might know.

In addition, we might also assume that the input for this filter could go in the form of knowledge of knowledge of knowledge of f itself. This knowledge of f, it does not mean either I know all of f, some kind of a generic knowledge of f, what we call us really a prior. And they sent this, prior and all is needed whenever you try to solve an inverse problem, it encounters issues of numerical stability, and now in order to overcome this numerical stability issue, it is imperative that we supply to this filter, to this restoration filter as much know how as we have about f, about noise, about h, whatever we know.

For example, even h for example, impulses this one, we might either know it completely, or let us say that we might have some clue about that it is a motion blur or optical blur, whether it is sparse or isotropic. So, all this information will all, they will all, they will be some kind of a prior. That again noise, we might know something about noise, to be noise variance, do we know that it is 0 mean, those kinds of statistics.

So, so so the entire block, so here, so when I write prior, I could be prior about f, prior about prior about h, prior about n, and prior prior about f, the interesting thing is even even giving a generic prior about f, something as simple as suppose you asked what would be a generic prior? So, simply say that local intensity should look similar that would be the generic prior, the Markovian kinf of a prior, which we have seen before something as simple as that, something I mean you know, which is something that holds true across all images. It does not have to be, it does not have to be just a face image or something. It could occur across natural images and so on.

Simply adding a prior like that can can actually pick up and stabilize your solution a lot because without these priors any attempt to solve this kind of ambiguous problem will lead to an effect that can be very noisy. We will see all of this as we go along. And therefore, at one tries to one tries to regularize the solution. Regularization is again something which we will see along the way. So, one tries to regularize the solution in the sense that this is that, in the sense that, we would not give more and more information about f.

So, that so the algorithm that is trying to solve for f, we can actually guide it towards a solution that is more sensible than some kind of solution which is extremely noisy. Now, now now when we talk about really deblurring, when h is known, if h is completely known, in some cases, it may be possible to know h completely, we call it a non-blind deblurring problem. And when h is when h is not known, it is unknown, we call it blind deblurring, we call it blind deblurring.

So, in this in this course, we will only be doing NBD which this, which it is not likely, we will assume we know h. Maybe I will maybe drop your, rock hinge along the way. So, how do you, how do you solve a blind deblurring problem? But really our focus will be on the situation when I know h completely and then I want softer f, even this is going to be hard. And and of course another assumption that we are going to make is we have a space in variant flow, because even this you will understand, you will realize, it is not, it is not easy at all, and it would require require a lot of effort to even solve a simple problem like this.