Medical Image Analysis

Professor Ganapathy Krishnamurthi
Department Of Engineering Design
Indian Institute Of Technology, Madras

Lecture 14
Framework

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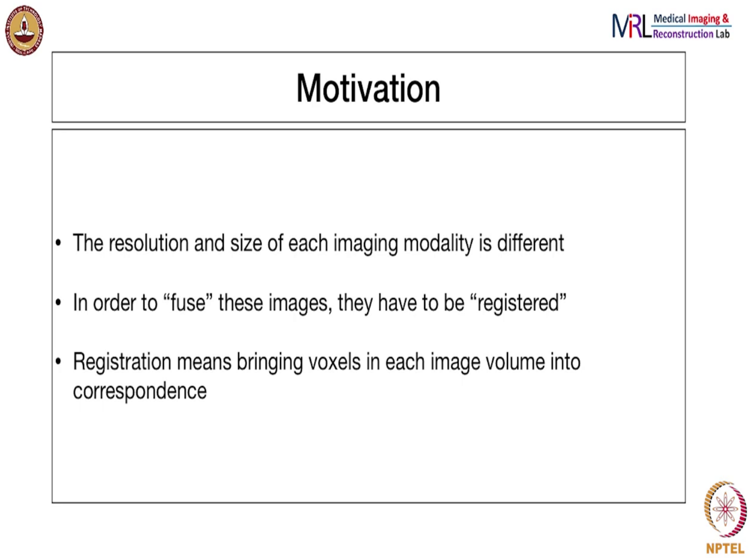

Hello, and welcome back. So, we are going to pick up from where we left a last time introduction to image registration. So, the general idea we summarized and so what does images station accomplished? What is in twice so important so what happens is typically, like I said, there is a, some patient post might change between different imaging time points.

And, the contrast mechanisms are different if the images of the same patient exists, but with different imaging modalities. So, in general, the idea is to bring the resolution and the size of images, take I mean, but taking into account the resolution and the size of each imaging modality.

And we would like to fuse these images, but before we fuse them, we make sure that they can be aligned on top. And this means that the, bring the voxels in each image volume into correspondence, so this can be done in intra-patient. In the sense, it is a same patient over time, or with different imaging modalities. And in some clinical studies, you will have to do this, inter-patients. So, you will have a bunch of patients where they are all image with the same imaging system.

So, let us say MRI of the brain, but then still have to fuse them to get like, let us say an exemplar image. So, in that case, you will have to align them and then fuse them so that for all those purposes, we do need medical image registration.

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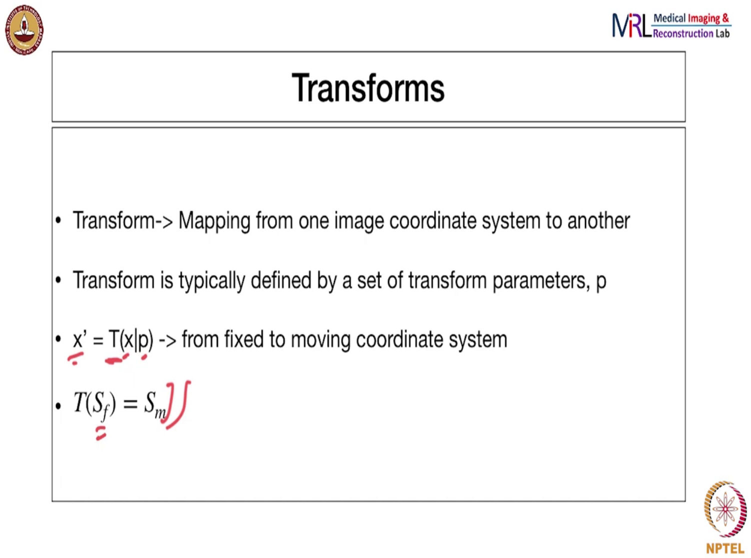

The important aspect here is the transformation that is we would like to transform one image coordinate system to another in the sense we have let us say an image taken at time 0.1 and we have another image taken time 0.2 be the way to bring them into corresponds is to figure out a coordinate transformation for mission between these two imaging coordinates.

And usually afford rigid transforms, this is a parametric transformation. So, there is a bunch of parameters p which parameterize a transformation and the way it is represented is shown here. So, we will typically show the transform denote the transform by T, so it takes x and it is also parameterized by p to get x' that is x' = T(x|p) .

So, it is basically starting from the fixed image coordinate system. So, that as like you act you take one image as reference and then it has its own coordinate system. So, from for each coordinate in that coordinate system you apply this transformation to get to go from the fixed image to the moving image coordinate system.

So, typically, if you apply the transform to the fixed image coordinate system in whole you should get the moving image coordinate system. So, we will see how this is useful in the sense what is the exact process but just wanted to introduce you to the important aspect of registration this is the transform itself.

So, in the case of rigid transformation, there is typically one set of parameters which are used for all the pixels. And there are transformations like non-rigid transformations, wherein you will have for every pixel voxel, there is an independent set of parameters and then makes the problem more complicated.

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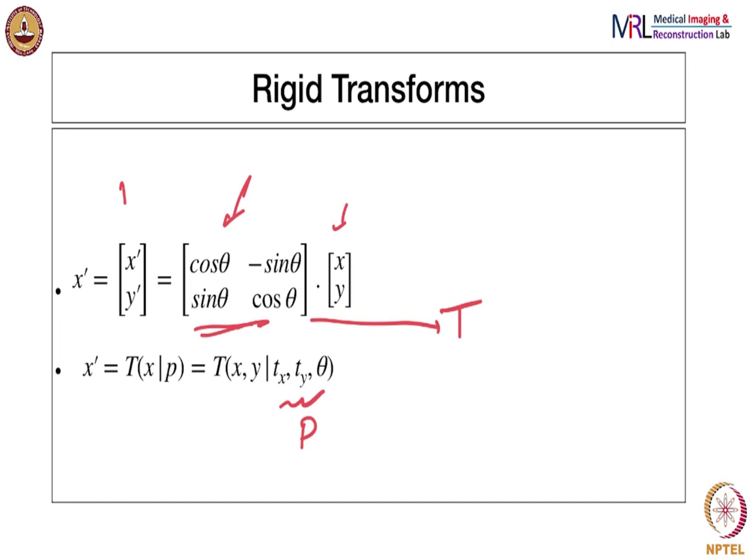

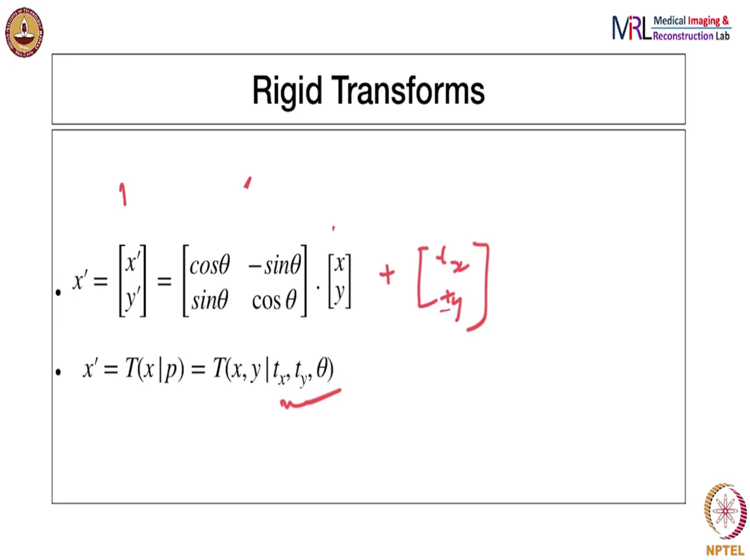

So, what is this transform that I keep talking about so very simple transformation is a rotation metrics. So, this is the rotation metrics. If you do if you rotate your coordinate system by let us say an angle θ, you should be a new coordinates x or given by this formula. So, if x and y or your existing coordinates, and you rotate the coordinates through an angle θ around the z-axis, let us say then your new coordinate (x’,y’) in terms of the old coordinates are given by this transformation metrics.

So, this is your transformation metrics. And the parameters of the transformation are here. These are the parameters of your transformation which are, this case, I have not shown t_x, t_y but you would have let us see, if you have like the hand like a translational components, so for instance, t_x and t_y translational components, I will just show you briefly how that works.

So, you would add them, so you would say plus t_x, t_y. So, this would be then the parameters of the transformer t_x, t_y and θ. So, this is the kind of transforms you would like to estimate using, rigid transformation technique. So, when you are applying the same kind of a affine transformation, in this case, just a rotation plus a translation.

There are of course other transforms which you use skew and shear which we call affine transformation, that is also available plus there is also scale in transform we will see them in the next over the course of the next few lectures.

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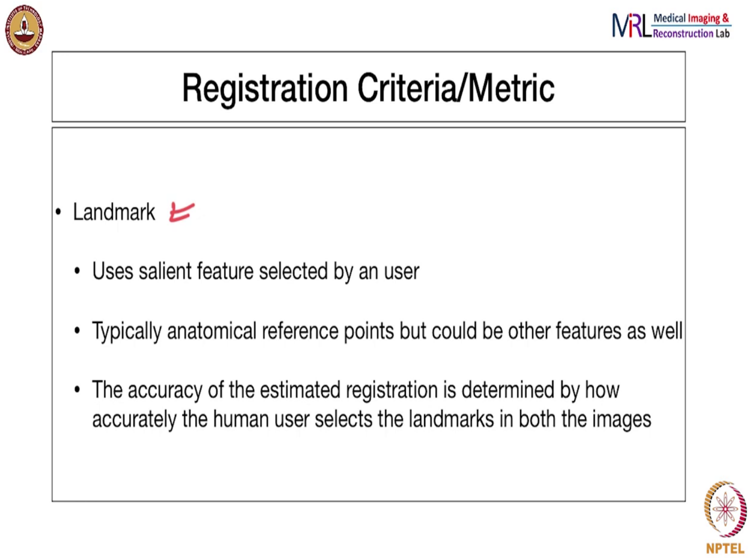

So, what else is required? So, we know that we have to estimate a transformation. And then we have to model the transformation. Using a set of parameters, I showed an example, which is typically the case, you use a rotation metrics and you have a translation vector, you have a scaling factor, typically and then if you are using affine transform, we have a couple of other elements which define these skews and shear. The other important thing is, what are we used to how are you going to estimate this transformation?

So, for that, what do we need to estimate the transformation? So, in order to estimate the transformations, we need some in one case, we can use landmarks. So, what do you mean by landmark? In the sense the user in this case and experience condition has to select a salient feature in every image. So, we have a fixed image and a moving image.

And, for instance, let us say the image of the skull of the brain it includes a skull, so the user has to choose control points in the skull, so the same control points in the two images. So, then we would know when twins user choosing it, then we know the coordinates of those two. So, two sets of points so, if you select a bunch of points that way, and then use those points to estimate the transformation.

How would that disadvantage shares, since it is user selected, the location of the control points that one is selecting or the salient points that one is selecting, is this depends on the user's in ability. So, there will be errors introduced, you are not going to be able to select exactly the same feature on both the images at the, I know, at the same point, it is very difficult.

So, the same exact when I say same exact point, I am talking about the anatomical reference here. So, it is very difficult to put the put your x or where mark the spot, exactly in both the images. So, those errors will propagate, when you try to estimate the transformation, but then landmarks can also be introduced automatically this time talking about intrinsic landmarks.

The other ways you can also use introduce extrinsic landmarks by having some form of, marker attached to the patient. So, for instance, during brain imaging, the use of something called a stereotactic frame, which they which goes the same way every time the which are goes on to the patient's, said the same way every time are the patient's image for the I am the stereotactic frame itself has a bunch of reference point would show up as very bright in the image and those can be localized very accurately in both in our fixed as far as moving images and those will give you the points for registration.

So, here is the trick is to choose a large number of these points more than the fixed and moving image and then estimate the parameters of the transform and using some least squares technique. So, that gives you a very robust estimation, it will also be able to estimate the errors in your transforms etcetera. So, using this technique, so, a landmark is a very good way of doing this.

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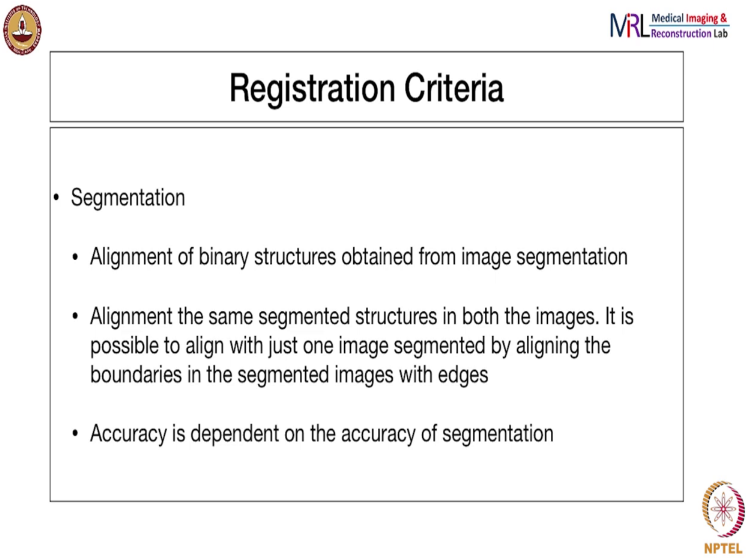

There is another way which is segmentation. So, segmentation is basically labeling all the pixels belonging to a certain anatomy. So, if you are able to label into both the fixed and moving images or, specific anatomies and, labels am I says 0 1 2 3 then all I have to do is to figure out the transform which maps all the zeros to zeros 1-2, 1 and 2, 2-2, 3-3 and so on.

Sometimes you might not be able to label all both the images, then you just do edge detection on other and then try to just match the edges. So, that is another thing and once again here, the problem is, the accuracy of the registration depends on the accuracy of the segmentation, which might not be a good thing.

So, but if the segmentation is very reliable in certain images, for instance, segmenting bone, a lot of times a simple thresholding works really well. So, then maybe sometimes when the segmentation can be reliable, you can still use this method.

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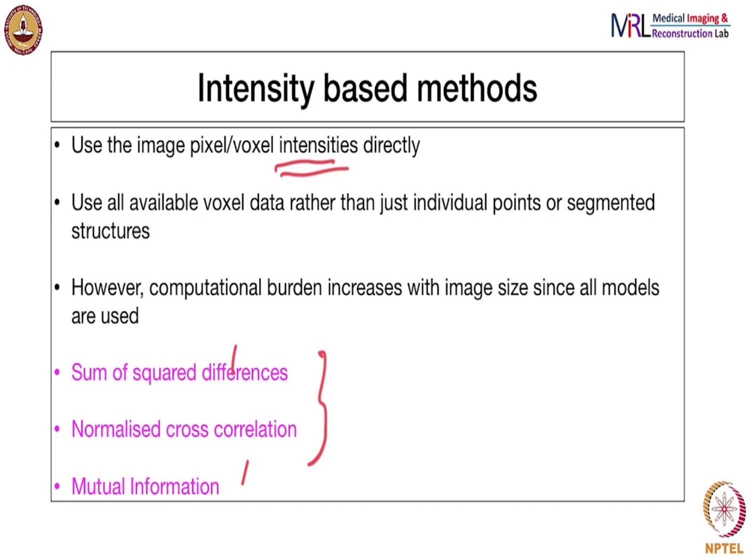

The intensity based methods very commonly used, especially inter modality inter-patient, because, it uses all the image pixel voxel intensities directly. Intensities in one form or the other either directly at point wise pixel densities or in the form of histograms. We will see that later. So, it uses all the data, so it means computationally intensive, so which means that if you have a very large image for the 3-D image, you will have a lot more pixels.

So, then, your competition burden increases. These methods, typically what they do is they use a loss functions, which tell you how good your transformation is. So, you are trying to estimate a transformation metrics. So, every time let us say you get one transform, and you apply it to the moving image.

And what you get is basically another image and you would like to see how good it how good is your transformation, then you can use these metrics typically sum of squared differences, normalized cross correlation, as well as mutual information in order to figure out how good your transformation is and then you iteratively refine your transformation in order to better these metrics.

So, this is another way of doing it other than using landmarks that is. So, this is the one that we studied more in depth right now, it is not the landmark based one of course, you are welcome to look up references, but we will look in this lecture some of these loss functions, I like to call them loss functions, we will call them metrics.

But these are this is the terminology is often used in medical image registration. So, basically, the idea is you have to find a mapping or transform from fixed image to moving image and in order to find that transform, you have to use we have to show some information from the images and these information could be in the form of landmarks or segmentations or just the plain intensity of the pixels.

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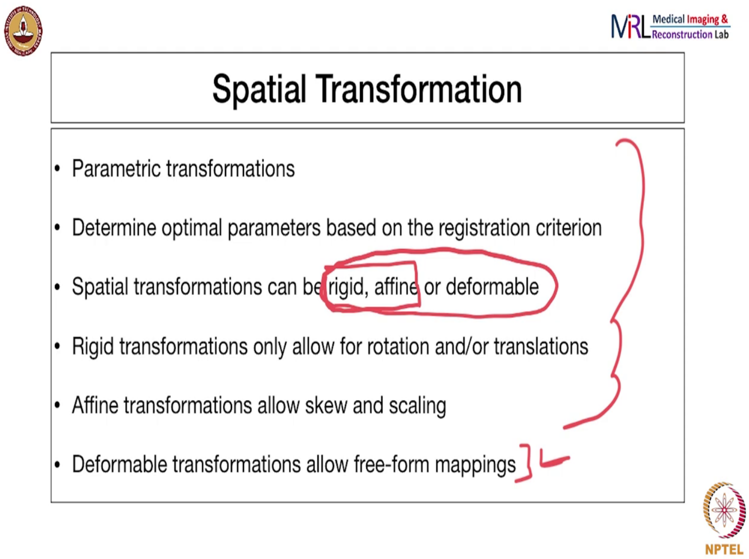

So, what kind of spatial transformations are we talking about? So, we are looking at all of these right now and we will look at this next week the deformable ones next week. So, when I say all of these, I basically meant rigid affine or deformable, I put the wrong bracket there. So, this is the one these are the ones that we are looking at, but specifically this week, we will look at rigid and affine.

So, these are this is because they are most-most often use. Because, rigid transformation allow for rotations and translations. And if you add affine you have skew scaling, shear, whatever you call it. Deformable transformations means it allows for free-form, like for instance, it is like, thick of leafed like, like jello, you can mold it like either any way we want.

Like dough, in fact, play though for instance, you can mold it anyway you want that kind of transformation. Of course, that is the big makes the process more tricky, and you need regularization and all that. So, we will look at this next week, but this week, I want to look at rigid enough a transformation.

So, they are kind of looking at the space of transformations that will satisfy the criteria, we looked at, sum of squared differences, normalized cross correlation or mutual information. And, we bring the images into alignment.

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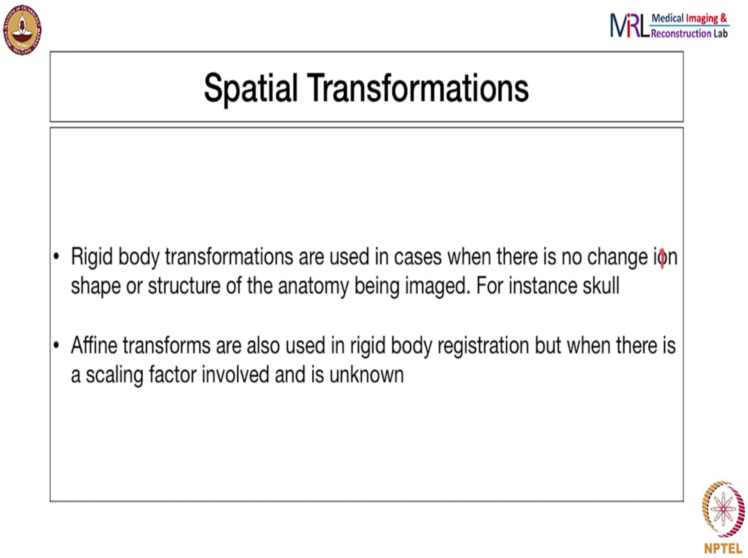

These especially rigid body especially is used when there is no change in sorry, there is a big spelling mistake here, a change in shape or structure of the anatomy being imaged and in the sense, you are looking at skull typically, you cannot say that about most except for the bone you can see that what most anatomies they do deform a bit lie down and you do not like on the same way every time.

And for instance, affine transforms are use also used in rigid body registration, but in this case some sort of scaling factor is involved and is unknown. So, then you kind of use affine transforms, but typically rigid transformation which just include rotations and translations, they are the ones that all typically used.

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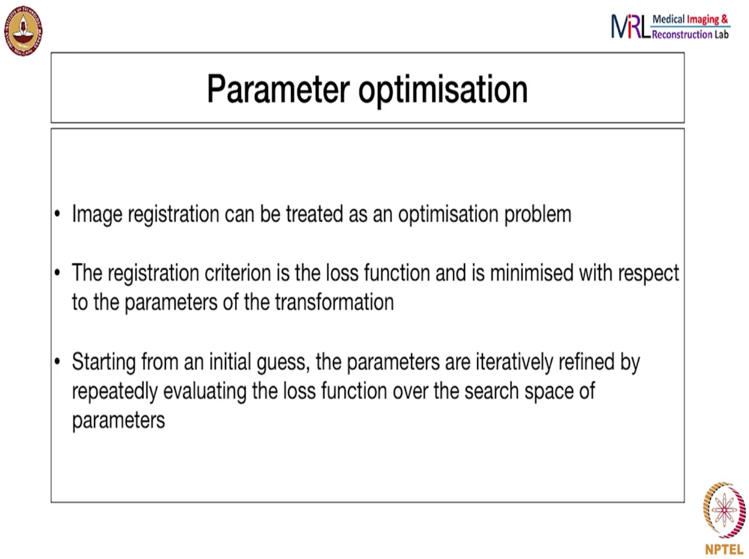

The last step so, like I said, we are trying to estimate iteratively estimate the parameters of the transform by looking at the matching criterion and seeing if, the matching criterion is improving. Improving in the sense it can be either decreasing or increasing depending on the kind of matching criteria you are using.

And how is this possible? It is possible by treating the image registration problem like an optimization problem wherein you try to minimize this matching rate you are maximize or optimizing the matching criteria with respect to the parameters of the transformation. So, you start from an initial guess and you kind of update the parameters. So, that the optimization criteria in this case the matching criteria is minimized or maximized.

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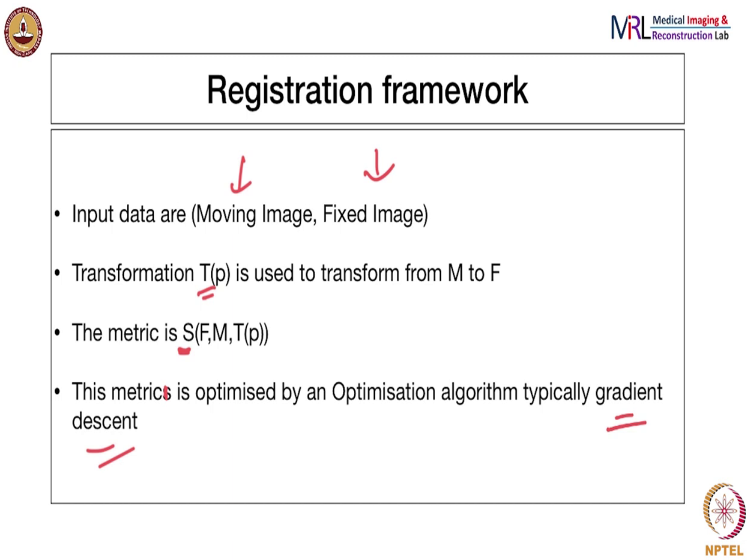

So, having said all that, here is the general frame or registration framework, which applies to any kind of image registration that you run into, you need input data, which consists of the moving image and the fixed image and as the name implies, the fixed image you do not do any transformations to it.

You will of course, apply the transformation metrics to the coordinates of the fixed image and then you will resample from the moving image we will see where the re-sampling part comes from later the transformation you have a model of the transformation that we need. The metric S the transformation typically is referred to as T, T is the parameter, parameters of the transformation.

So, this and then you have the metric this metric sorry again filling mistake this metric is optimized by some optimization algorithm typically, gradient descent works very well for some of these problems. So, use gradient descent to update the parameters in order to minimize or maximize this metric. So, this is the typical registration framework.

And this is what most effect all registrations will follow this in some form or the other. So, what we will do is, before we go any further, we will look at the, coordinate systems we will be working in. And once we know, once we understand the coordinate system will be working in then we will look at, what are the different types of transformation, especially for rigid registration? What kind of transformations are allowed? What kind of metrics are meaningful? Especially, we are only going to look at intensity based metrics.

Optimization algorithm, we would not go into detail. In fact, I will just mentioned this in passing, I already mentioned it, typically some form of gradient descent would typically work very well. So, we will, look at these various components from the next few lectures.