

# Digital Image Processing

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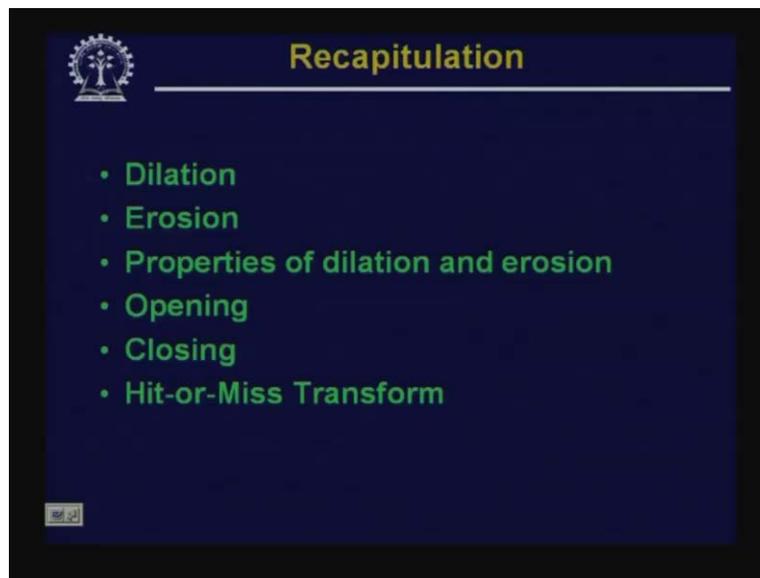
Indian Institute of Technology, Kharagpur

Lecture - 35

Mathematical Morphology- III

Hello, welcome to the video lectures series on digital image processing. For last few lectures, we are discussing about the mathematical morphology and its application to image processing problems.

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So, in the last class, what we have seen is we have seen what is meant by morphological dilation operation, we have also seen what is meant by morphological erosion operation and with few examples, we have illustrated that the dilation operation if I have a binary image and within the binary image in the object region if I have some background pixels, some pixels which are treated as background and this may happen because of the presence of noise; in that case, the morphological dilation operation tries to remove those noisy pixels which should have been the object pixels but because of some noise which have converted which have been converted to be the background pixels.

And, we have seen the side effect of this dilation operation that as the dilation operation tries to remove the noisy pixels within the object area; at the same time, the dilation operation tries to expand the area of the object region and the reverse operation that is the morphological erosion

operation that we have seen that it tries to remove the spurious noise present in the background region and at the same time, as the side effect the erosion operation contracts the object region. That means the area of the object region gets reduced as we apply erosion operation on a binary image. Then, we have also seen some properties of the dilation and erosion operations. Then we have seen the combination of erosion and dilation operations which are termed as opening and closing operations.

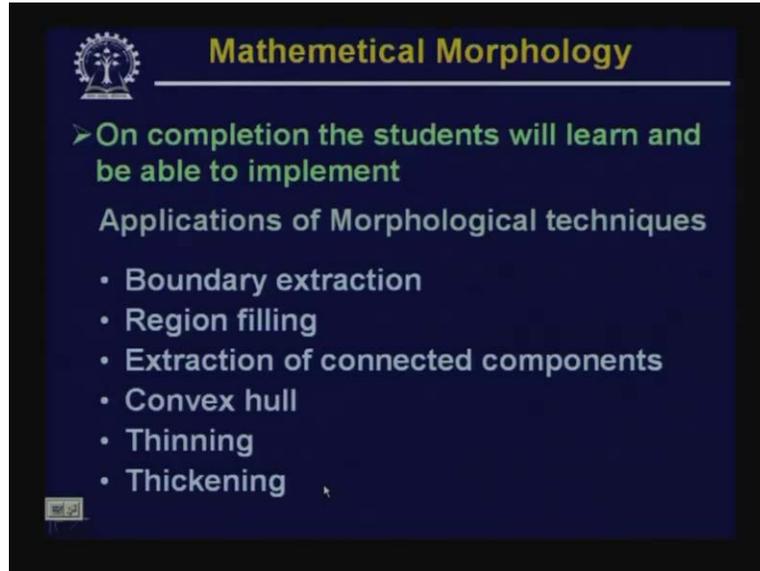
So, in case of opening, what we do is given a binary image and we have said that for all the morphological operations, our basic assumption is that an image should be represented by a point set. So, when I say that given a binary image or given a point set; the opening operation, what it does is first it performs an erosion operation which is followed by a dilation operation and in the other case, in closing operation, first what you perform is a dilation operation which is followed by the corresponding closing operation and for all these operations when I go for the opening or closing operations, for all these operations we have to use the same structuring element.

Now, by application of this opening and closing operation, in our last lecture, we had taken an example where we had shown that suppose you have got two different objects; in one of the objects, there was a patch which appeared to be a background and the two objects were joined by a thin straight line. So, we assumed that these are because of noises; when two objects are joined by a thin straight line that is because of noise.

Similarly, within the object region if I have some pixels which are converted which appeared to be the background pixels, we also assume that this is also because of the presence of noise. So, by using the opening and closing operations on such an image, we have demonstrated that such a kind of noise can be removed and at the end, what we had obtained is two different regions belonging to two objects.

And then finally, in our last class, we have talked about another kind of transformation, the morphological transformation which is termed as hit or miss transform. And, we have illustrated that purpose of this hit or miss transform is to locate an object of a specific shape and size within a given image. So, in that case, what we have done is we assumed that the object of the specific shape and specific size is treated as a structuring element and we try to find out the presence of such an object within the given image and for that we have used the combination of erosion and dilation operations and which is termed as hit or miss transform.

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In today's lecture, we will talk about some applications of some further applications of morphological techniques. The first operation that we will discuss is a very simple operation which is boundary extraction. So here, what we will try to do is that given a binary image containing some objects, we are interested in finding out the boundary of the object region. Now, in the earlier case, when we discussed about the different edge detection operation or different line detection operation; in that case, we have found different operators like Sobel operator, Prewitt operator, Laplacian or Gaussian operator which can be used to detect the object boundaries.

In today's lecture, we will try to address the same problem from the mathematical morphology point of view. So, we will try to devise some algorithm, some morphological algorithm by which the boundary of an object region can be detected. The second problem that we will talk about is a region filling operation. So, if I have just the boundary of an object, we will try to see whether it is possible by using the morphological operations to fill the entire region, entire object region which is enclosed by boundary pixels.

Then, we will also try to find out some algorithm for extraction of connected components. So here again, in one of the earlier lectures, we had talked about some algorithm for connected component level. So, there the problem is that if you have a set of points which are similar in nature and they are connected, then what we try to do is level all the pixels, all such pixels with the same level value or you give a unique identification number to the region to the entire region which is formed by all those connected pixels having similar values.

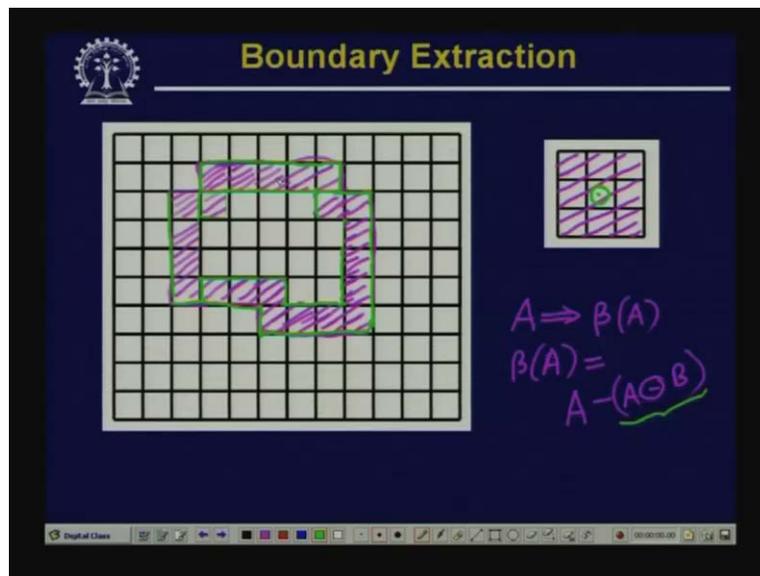
So, in this particular case, in this lecture, we will try to find out an algorithm for extraction of the connected components in a binary image. Then, we will talk about another operation, another algorithm which is for convex hull extraction. Now, convex hull is a property, we will define later on that what is meant by a convex, a set to be convex and what you mean by convex hull.

And, this convex hull is very important, gives you important information for high level image understanding operations or object recognition operations and we will see that how we can find out the convex hull.

We will see what is convex, what is meant by a set to be convex and we will try to find out we devise an algorithm to find out the convex hull of a given image or a point set. Then we will also discuss two more algorithms; one is thinning and the other is the thickening operations. So here again, given a point set, an image; we will try to find out algorithms, how to thin that image because in one of our earlier lectures we have said that the structural information of an object is contained within the skeleton of that object shape and for that earlier we have said something about medial axis transformation.

So, this medial axis of an object region is nothing but a thinned version of the object shape. So here, we will try to find out that how we can thin an object shape or how we can thin a point set by using the morphological operations and thickening is of course, the inverse or the reverse of the thinning operation. So, we will also talk about how the thickening of a point set can be done. So, first of all, we will discuss about the boundary extraction operation.

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So, by boundary extraction, what I mean is suppose we are given an image like this, say my object region is the set of this shaded pixels. So, this forms my object pixels or the point set say A and what we are interested in is to find out the boundary of this object region. So, for a given set say A, this is the point set, I can represent the boundary of this point set as say beta A where beta A represents the boundary of the given point set A and this beta A, it can be shown that it is nothing but the set A minus A eroded with sum structuring element B.

So, what we mean by this let us assume that we have a structuring element which is as given here. So, this is my structuring element and I assume that the center of the structuring element or the origin of the structuring element is the center pixel. So, first operation that we will perform is this

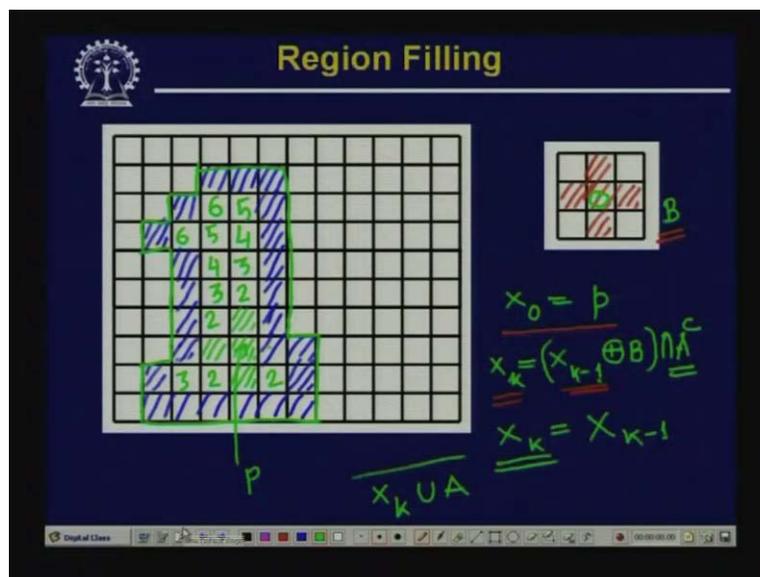
that is we will erode the point set A with this given structuring element B by 3 structuring element and you know that when we try to erode this given shape with this 3 by 3 structuring element; then as we have said earlier that this erosion operation contracts the area of the object region and by performing this erosion operation, we will find that all these boundary pixels will be deleted because of contractions. So, all of these pixels are going to be deleted, all of these pixels are going to be deleted after we erode this point set A with this particular structuring element.

So now, if I take the difference if I subtract the output of this erosion operation from the original point set A, then because all these boundary pixels have been removed because of this erosion, after doing this set difference operation, you find that all these internal pixels which were there as part of erosion; all these internal pixels are going to be removed.

So finally, what we are left with is as is obvious on this figure is boundary of the object region. So, here we find that boundary of a given object region can be very easily determined by performing the erosion of the original set, original point set A with a 3 by 3 structuring element and finally what you have to take is you have to subtract the erosion, the eroded image from the original image and then what you are left with is the boundary of the given object region.

So, this is a very simple operation. Now, let us try to find out that just opposite to this that if we are given the boundary of an object region; how we can fill up the hollow region within the boundary again by application of morphological operations? So, let us take another example for this operation.

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So here again, let us assume that we have an image say something like this. So, this is our given point set. So, here we find that we have a set of pixels which forms a boundary and within this boundary, we have a hollow region which is simply represented by white pixels and what we will try to do is we try to devise an algorithm by which this internal hollow region can be filled up. So, for performing this operation, the kind of structuring element that we can use is something like

this. Again, we use a structuring element within a 3 by 3 window but for in this structuring element, you find that the diagonal neighbors of the origin; here again we assume that origin is the center pixel of this 3 by 3 window and in this structuring element, we do not consider the diagonal neighbors of the origin.

Now, for region filling operation, what we have to do is first let us consider say any pixel P within this hollow region. So, I consider a point within the hollow region and let me call this point as the point P and our algorithm will be something like this; first we set this point P is equal to 1 and I take and I assume assign a point set say  $X_0$  where  $X_0$  is initially the point P and a region filling operation will be performed by iterative application of dilation operations.

So, the algorithm for this region filling operation in the form of an iterative algorithm can be written like this; say at stage at the iteration stage k, I say that  $X_k$  will be given by  $X_k$  minus 1, dilate this with our structuring element B. So now, in this case, this is our structuring element B and what we do with this dilated point set is that we take the intersection of this with the complement of the point set A.

So, these are the points in our point set A and obviously **the complement of this will be** in the complement all this points will be made equal to black and all other points will be made equal to white. So, if I do this particular operation, let us see how this algorithm is going to work. So initially, what we have done is we have assumed that our  $X_0$  is equal to is just the point P and next what I do is I dilate this  $X_0$  following this iteration that  $X_k$  is equal to  $X_k$  minus 1 dilation with B and take the intersection of this with A complements.

So, if I dilate this  $X_0$  with our structuring element B as given over here; in that case, you find that these are the points which will be set equal to 1 and since this has to be intersected, so this point also will be set equal to 1 but since we will take the intersection with A complement, in A complement **this point will be equal to** this point will be black. So, if I take the intersection, this particular point will be removed. So, what I have?  $X_1$ ,  $X_1$  is all these points.

Now, what will be  $X_2$ ?  $X_2$  will be dilation of all these points. So, if I just give the level, say these are the points which will be made equal to 1 after performing dilation in the second iteration. So, these are the points which will be made equal to 1 after performing the second iteration and taking the intersection with A complement. These are the points which will be made equal to 1 after the third iteration and performing the intersection operation. These are the points which will be made equal to 1 after the fourth iteration and performing this intersection operation. These are the points which will be made equal to 1 after fifth iteration and performing this intersection operation and these are the points which will be made equal to 1 after sixth iteration and performing this intersection operation.

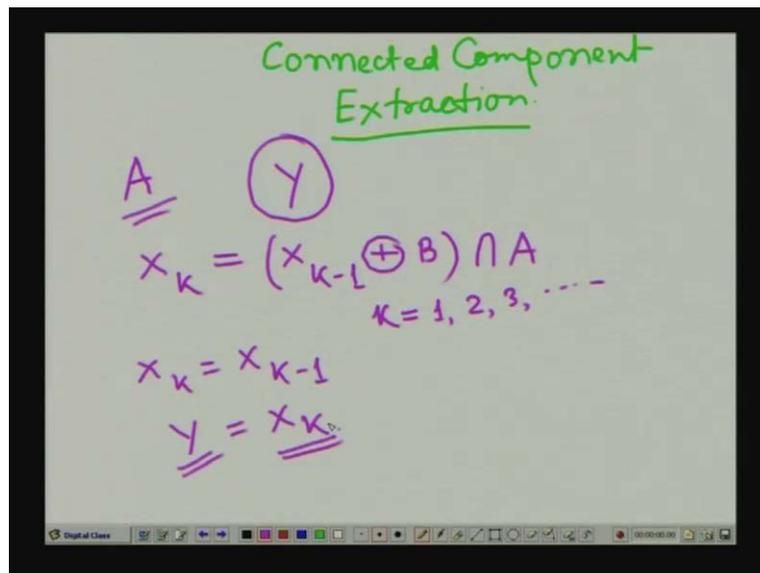
Now, we find that once I get this, if I perform for the dilation with the same structuring element and followed by intersection with a complement, this set is not going to change any further. So, I achieve a convergence when I find that  $X_k$  becomes equal to  $X_k$  minus 1. So, when I get the point set identical point set in two subsequent iterations, that is my point of convergence and at that point of convergence, whatever  $X_k$  I get, this  $X_k$  is nothing but all the points, this  $X_k$  contains all the

points which are filled up because of this iterative operations and finally, the final set will be when I achieve this convergence, the final set will be given by  $X_k$  union with our original point set A.

So, at the end, you find that all these points within this boundary, they have been made equal to 1 and you will find that such a region filling operation is very very useful when we talk about it will be seen that when we talk about the object description or object representation, we realized that this kind of region filling operation is very very important because unless we do such a kind of region filling operation, our object description will not be compact. So, you find that we have devised a very simple algorithm for performing the region filling operation.

The next kind of algorithm as we have said the morphological algorithm that we will discuss is the connected component extraction algorithm. Obviously, we have talked about the connected component leveling problem earlier but here the same problem we will tackle with the morphological operations.

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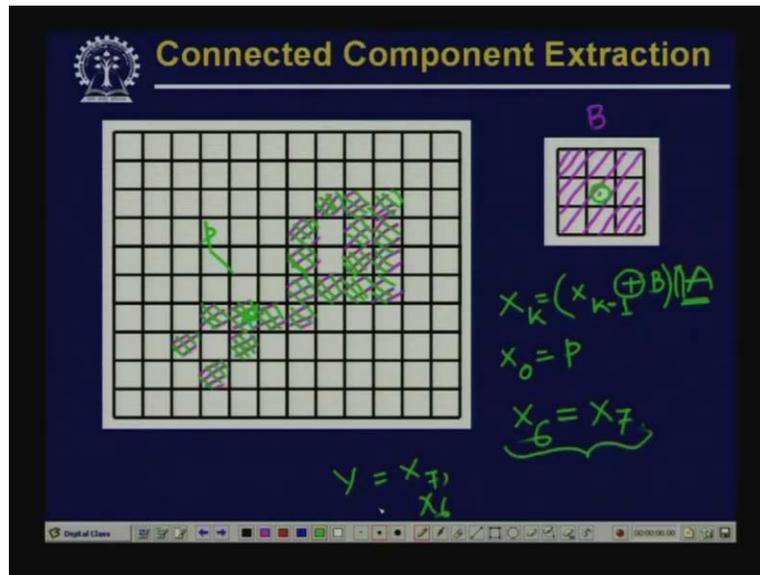


So, let us see how this connected component extraction can be done. So, here again, we are given a point set A. So, we are talking about the connected component extraction. So here, we are given a point set A and suppose Y is a connected component in set A. So, you are given a set of points a point set A and we assume that this Y is a connected component in A; so what we will try to do is we will try to extract all the points which belong to Y where Y is the connected component. That means we are trying to extract all the connected points of a subset of A which is connected. So here, this subset is our connected component A.

So here again, we will use the similar kind of iterative algorithm and now our algorithm will be something like this, say the iterative algorithm will be  $X_k$  is equal to again you take the result from the previous case, the previous iteration  $X_k$  minus 1, dilate this with the structuring element B and this dilated result has to be intersected with the original point set A and this operation has to be computed for various iteration steps. So, it has to be done for say K is equal to 1, 2, 3 and soon.

Finally, as before, we reach a convergence or the algorithm will terminate when we find that  $X_k$  remains same as  $X_{k-1}$ . That is in two subsequent iterations, the result does not change and at that point, the algorithm terminates and in that particular situation when the algorithm terminates or you reach the convergence; in that case, we will find that  $Y$  is nothing but  $X_k$  where we said that  $Y$  is the connected component in the point set  $A$  and by this algorithm, we have been able to include all the points in set  $A$  in our point set  $X_k$  which we achieve at the end of the algorithm or when the algorithm converges.

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So again, let us take an example for this. So, what we will do is as before, let us take a particular set of connected pixels, so something like this. So, these are the set of connected pixels and I assume a structuring element  $B$ , this is my structuring element which is a 3 by 3 structuring element and as before, I assume that the origin of the structuring element is the center point.

So here, what we have said is our iteration algorithm is something like this; we have to have  $X_k$  is equal to  $X_{k-1}$ , dilation of this with our structuring element  $B$  and this has to be intersected with our original point set  $A$ . Now initially, what we do is I take a point  $P$ , say this is my point  $P$  which belongs to  $Y$  and I initialize  $X_0$  is equal to point  $P$ . Now, again from here, you find that because  $X_0$  is equal to is nothing but our point  $P$ ; so if I dilate this  $X_0$  with our structuring element  $B$ , then what I am going to get is  $X_1$ . After doing this dilation, if I intersect that with our original point set  $A$ , then what I am going to get is nothing but the point set  $X_1$ .

So here, this being our initial point  $P$  if I dilate this with this structuring element; in that case, you find that all these points are going to be set to 1. But after dilation operation, as I am taking the intersection with our original point set  $A$ , we find that only points which will be in set  $X_1$  at the end are only these points.

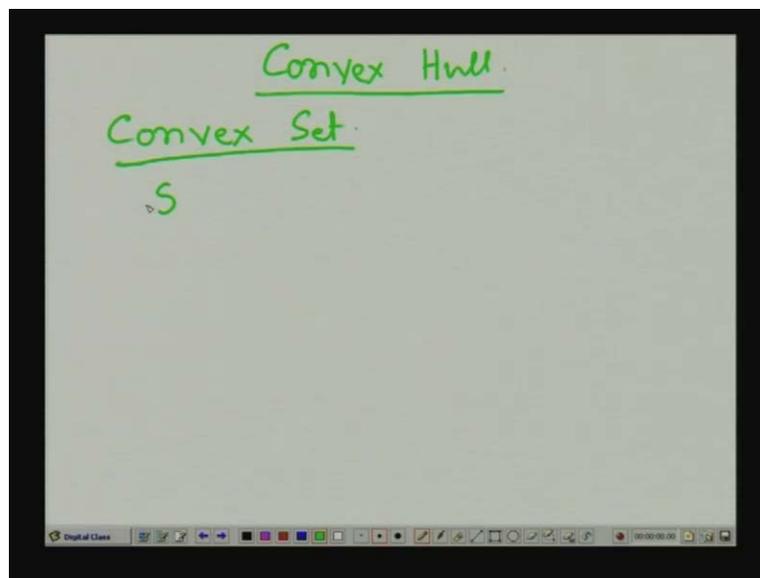
So, these are the points which are going to be in our set  $X_1$ . If I dilate this further, then these are the points which are going to be in set  $X_2$ , if I dilate further and do the intersection, then these are the points which are going to be in set  $X_3$ , do it further, then these are the points which are going to be in set  $X_4$ , dilate it further, these are the points which are going to be in set  $X_5$ , dilate it further, these are the points which are going to be in set  $X_6$  and further dilation and intersection operation is not going to change our  $X_6$  anymore.

So, you find that at that point, I get  $X_6$  is equal to  $X_7$ . So, this is our point of convergence and from this figure, from this output, what you observe say that when I reach this point of convergence; in that case, as I said that our original connected set of points, the connected point set  $Y$  is nothing but our point set  $X_7$  which of course is same as point six point set  $X_6$ .

So, you find that when this algorithm converges, then the points all the connected points in set  $A$  which is in our case set  $Y$ , this is the connected set of points; so all these points will be accumulated in the point set  $X_6$  which we have got as a result of this iterative operation of  $X_k$  is equal to  $X_{k-1}$  dilated with  $B$  and take the intersection with our original set  $A$ .

So, what we have done in this case is in this particular case, we have started from our original point set, we have started with the point belonging to the set  $y$  and then we have try to grow the region starting from that particular point. So, the next algorithm that we are going to discuss is what we will call as convex hull.

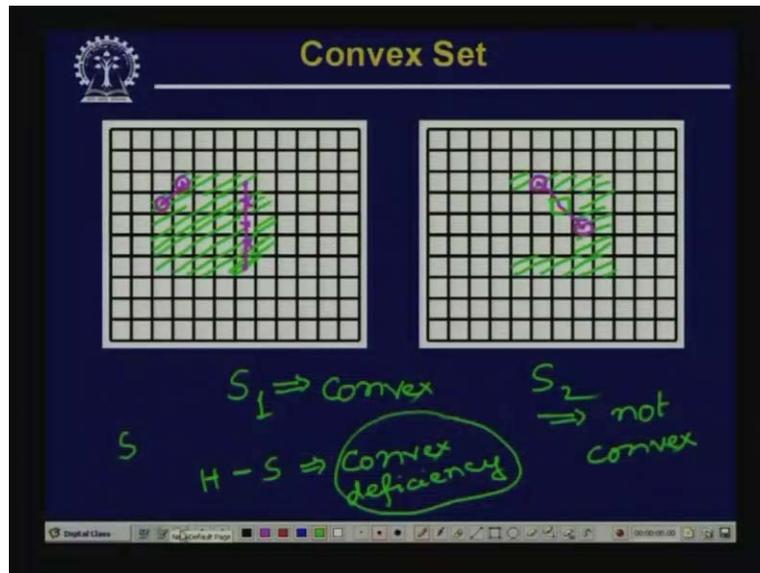
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When we talk about convex hull, the first thing that we have to see that what is meant by a convex set or what do we understand by a set to be convex. A set say  $S$ , a point set  $S$  is said to be convex if I take any pair of points, take any pair of points in the set  $S$  and join a straight line connecting these two points. So, if I find that all the points lying on this straight line also belong to this particular set  $S$ , then we will say that set  $S$  is convex.

Whereas, if there is any point on the straight line connecting those two points belonging to set  $S$ , so if there is any point on this straight line which does not belong to set  $S$ ; in that case, we will say that set  $S$  is not convex.

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So, coming to an example, say I have a situation something like this; say I have two sets of points say one set of point is something like this, this is one set of point and maybe I have another set of points which is something like this. So, this is my set say  $S_1$ , this is say  $S_2$ . You find that in this point set  $S_1$ , say suppose my set is something like this; so you find that in this point set  $S_1$  if I take any pair of points, any two points and join a straight line, draw a straight line through that pair of points, so something like this; you find that all the points lying on this straight line, they are within set  $S_1$ .

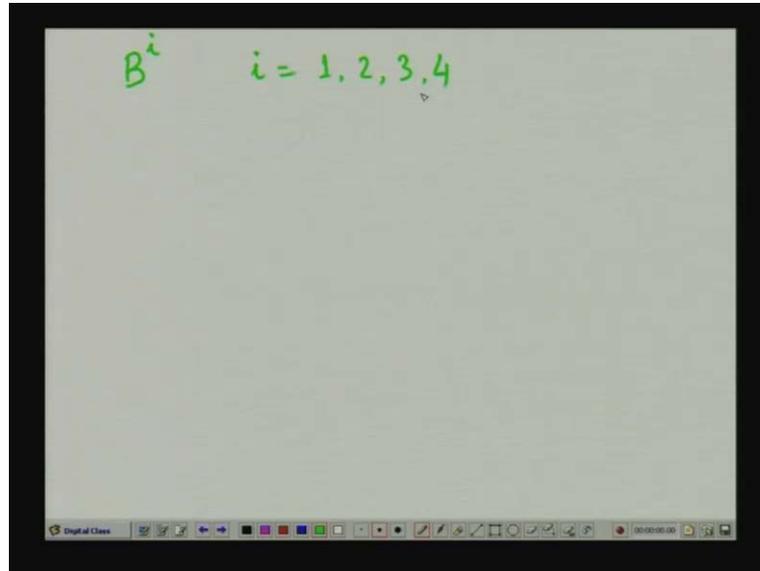
But here, in this particular case, if I take say these two points and join a straight line, then you will find that I have a point on this straight line which does not belong to set  $S_2$ . So, in this particular case, you will find that this set  $S_1$ , this is a convex set, you say that set  $S_1$  is convex whereas this set  $S_2$ , this is not convex.

So, given a set  $S$ , the convex hull of this set  $S$  will be the minimal set containing set  $S$  which is convex. So, that is how we define convex hull. Given any set  $S$ , the set  $S$  may be convex or it may not be convex.

So, a point set which contains  $S$ , some minimal point set that contains set  $S$  which is convex is called the convex hull of set  $S$  and if I say that  $H$  is the convex hull of set  $S$ ; then  $H$  minus  $S$ , this is what is called as convex deficiency. So, the difference, the set difference of the convex hull with the original set of points is called the convex deficiency and we will see later that this convex deficiency can be used as one of the descriptors of a given set which may be useful which is useful for high level understating purpose.

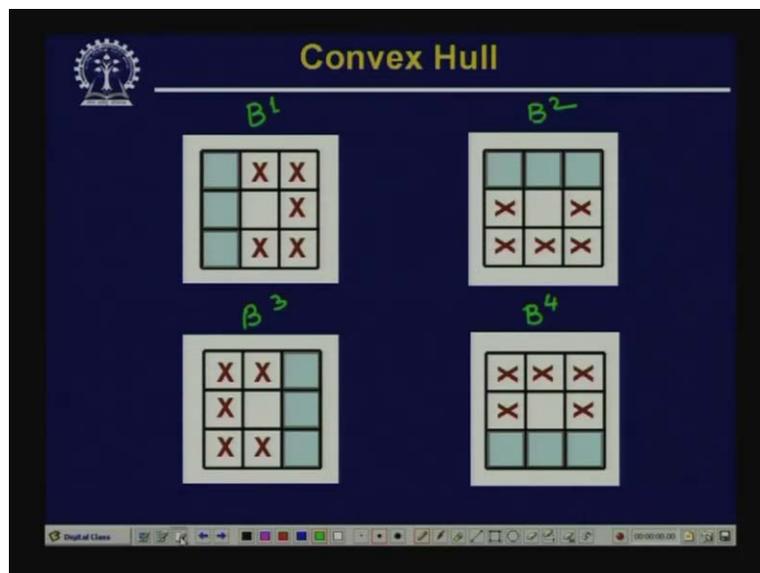
Now, let us see an algorithm, how we can devise an algorithm that given a points set S; how we can find out the convex hull of that given set S.

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So, let us see that what will be the nature of this algorithm. So here, instead of using single structuring element, we use a set of structuring elements. So, I assume that  $B^i$  is a structuring element where  $i$  varies from say 1 to 4. So, I use 4 structuring elements for performing in this particular operation.

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So, the 4 structuring elements which are used for determining the convex hull is as shown here. So, this is the structuring element, let us call this the structuring elements  $B^1$ , I call this say structuring element  $B^2$ , I call this the structuring elements  $B^3$  and I call this the structuring element  $B^4$ . So, I have 4 such structuring elements which will be used to find out the convex hull.

Then the algorithm for finding out the convex hull will be like this; I take a particular structuring element  $B^i$  and using that particular structuring element  $B^i$ , I go for a similar kind of iterative algorithm and this has to be this iterative algorithm has to be applied for each and every individual structuring element in our set of 4 structuring elements. So, the iterative step or the iterative algorithm will be something like this.

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$$X_k^i = (X_{k-1}^i \oplus B^i) \cup A$$

$$X_0^i = A$$

$$X_k^i = X_{k-1}^i$$

$$D^i = X_{conv}^i$$

$$C(A) = \bigcup_{i=1}^4 D_i$$

So, for a given structuring element, for a particular structuring element say  $B^i$ , we will perform an iterative algorithm like this say;  $X_k^i$  is equal to  $X_{k-1}^i$ . Take the hit or miss transform of this with the structuring elements  $B^i$  and then perform the union of this with our original point set  $A$ . So here,  $A$  is the original point set and this iterative algorithm has to be done independently for each of the structuring elements  $B^1$ ,  $B^2$ ,  $B^3$  and  $B^4$  and in this iterative algorithm, what is our initial condition? Initial condition is  $X_0^i$  is equal to our original point set  $A$ .

Now again, as before, the algorithm this iterative algorithm with each of the structuring elements will converge when we find that  $X_k^i$  is equal to  $X_{k-1}^i$ . That is in two subsequent iterations, the output does not change. So, in that case, our algorithm converges and if I say at that particular stage say, what I get as output is nothing but  $X^i$ ,  $X^i$  superscript because this is what we obtain with the  $i$ 'th structuring elements  $B^i$ , so I represent the set as  $X^i_{conv}$ . That means the output that I get when our algorithm converges and I represent this as set say  $D^i$ .

Then the convex hull of  $A$  if I represent this as  $C(A)$ , say  $C(A)$  is the convex hull of  $A$ , convex hull of  $A$  will be represented by union of  $D^i$  for  $i$  is equal to 1 to 4. So effectively, what we are doing? We are taking 4 different structuring elements, then for each of the structuring elements,

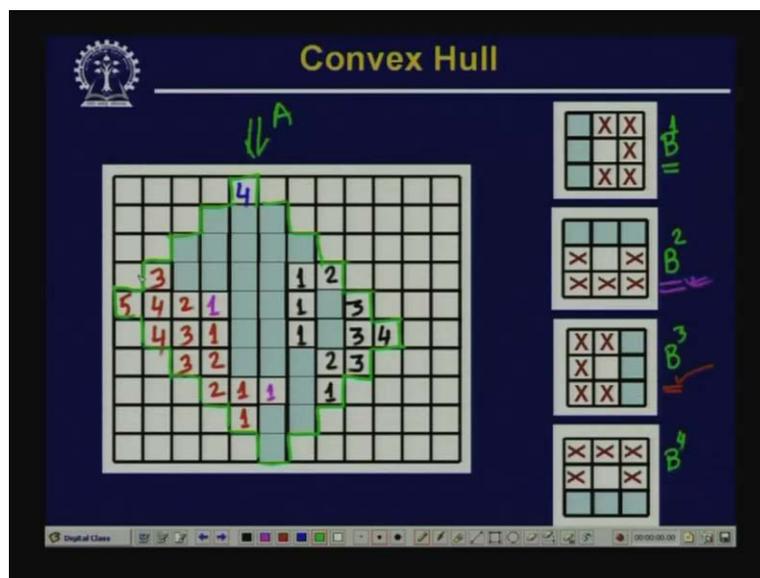
we employ an iterative algorithm. In every step of iterative algorithm, what we are doing is we are performing the hit or miss transform of our given set of the output at is this  $k$  minus 1 with the structuring element  $B^1$  and then taking the union of the output of this hit or miss transform with our given set  $A$  and after union operation, whatever output the point set that you get that is assigned to point set  $X_k$ .

So, we are generating  $X_k$  from point set  $X_{k-1}$  by hit or miss transform, by applying hit or miss transform with one of the structuring elements and subsequently doing the union operation with our original point set, the given point set  $A$  and this iteration will continue until and unless the algorithm converges and the algorithm will converge or convergence criteria is that in two subsequent iterations, the result does not change.

So, since we are having four different structuring elements, I will get four different point sets at the end of converges; when the algorithm converges, I will get four different point sets and the union of all those four different point sets is the convex hull of the given point set  $A$ . Now, let us see how this algorithm actually works.

So, as we have said earlier that these are the four different structuring elements which are used for extraction of the convex hull. Now, to demonstrate the operation of this algorithm, what we have is say we take an image like this.

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So, this is our point set  $A$  and these are the structuring elements, I call it the structuring element  $B^1$ , this is the structuring element  $B^2$ , this is the structuring element  $B^3$  and this is the structuring element  $B^4$ . So, what we want to do is we have to perform the hit or miss transform of this particular given point set  $A$  with these different four structuring element.

So, first of all, let us take the hit or miss transform of this given set  $A$  with the structuring element  $B^1$  and let us see that what we will be the nature of the output in each of the iteration

stages. To demonstrate this output, let us take different colours. So, all the hit or miss transform of this set A with this structuring element  $B^1$  will be represented in black colour. So, if I take the hit or miss transform of this set A with the structuring element  $B^1$ , then you find that in first iteration, these are the points which are going to be filled as you have marked with 1.

So, these are the points which will be filled **after applying** after the first iteration when I do the hit or miss transform with this particular structuring element  $B^1$ . Then, at the end of second iteration, these are the points which are going to be filled up. At the end of third iteration, you find that these are the points which are going to be filled up and at the end of fourth iteration, you find that this is the point which will be filled up. Similarly, when I perform the hit or miss transform of this same set A with respect to or structuring element  $B^2$ , then you find that at the end of first iteration, this is the point which is going to be filled up. So, I represent  $B^2$  with this pink colour, the output of hit or miss transform with this pink colour.

So, this is the point which is going to be filled up at the end of first iteration, this is also the point which will be filled up at the end of first iteration and if I do subsequent iterations on this point set, you find that I cannot fill up any other point. So, this is where I reach the convergence and this is the set union with my A, original set A that gives me the output set at the end of convergence with hit or miss transform with the structuring element  $B^2$ .

Now, if I take structuring element  $B^3$ . Now, I represent this as with red colour. So, with  $B^3$ , you find that at the end of first iteration; this is one of the points which will be filled up, this is another point that will be filled up, this is another point that will be filled up. So, this is what I get at the end of first iteration. At the end of second iteration, this is the point that will be filled, this is the point that will be filled up, this is also another point that will be filled up.

At the end of third iteration, this is a point which will be filled up, this is a point that will be filled up, this is also a point which will be filled up. And at the end of fourth iteration, you find that this point will be filled, this point will be filled and at the end of fifth iteration, this is the point which will be filled. So, we find that which structuring element  $B^3$  and in subsequent iteration, I cannot fill up any other point by performing the hit or miss transform with my structuring element  $B^3$ .

So, we find that when I reach convergence, by applying this structuring element  $B^3$ , then all these red set of points, all the set of points represented by this red along with the original set of points that represents the set of points that I get at the end of convergence with our structuring element  $B^3$ . Similarly, when I apply the structuring element  $B^4$ , now let me represent it in blue colour. So, with  $B^4$  at the end of first iteration, you find that these point, I can fill up but after this, when I go for second iteration, I cannot fill up any other point.

So, at the end of convergence, this is the only point that can be added to my original set and then what we have said is that when I reach convergence by performing that iterative algorithm with independently with each of the structuring elements; all those converged sets, I have to take union, I have to take union of all those converged sets and this output of the union, the point set that I get after performing the union operation that is what gives me what is called the convex hull of the given set A.

So, in this particular case, you find that all these points, all these points; it actually forms the convex hull of the given set A because if I take the union, then I get all these different points. These are all the points that I get. Now, you find that this particular algorithm has a drawback, draw back because when we defined the convex hull, we have said that it is a minimal set containing the set A but the set has to be minimal, I mean, the set has to be convex. So, it is the minimal set containing the original set A which is convex is called the convex hull of the given set A.

Now, if you look at this particular set, you find that it is not the minimal set. What I can do is I can remove these points from this set. So, these are the points that I can remove from this set. So, these are the point that I can remove from this set and the resultant set that I get is still a convex set. So, the minimal set is actually this set, not the set that we have obtained by applying those iterative algorithms.

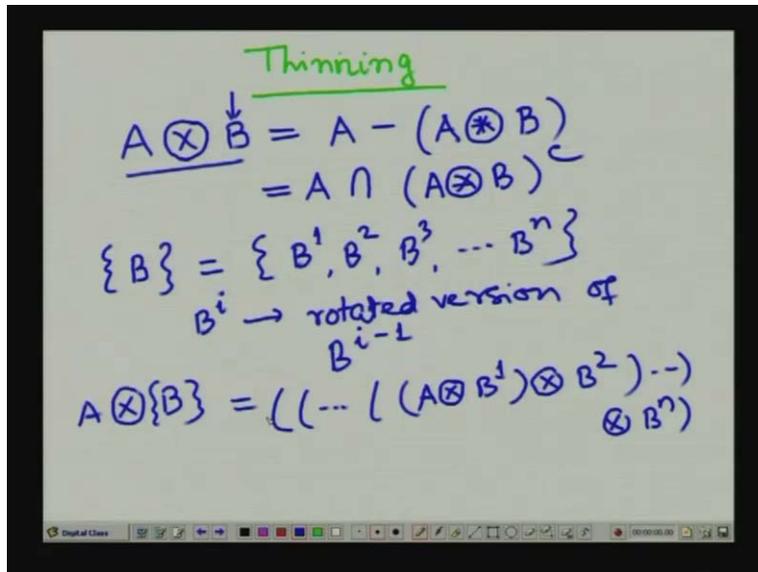
So, now the question is how we can get the real convex hull in the sense that the set is minimal? So, that can be done by limiting the expansion of the region beyond the horizontal and vertical limits of the original point set. So, you find that the horizontal and vertical limits of the original point set is like this; in the original point set in the vertical direction, I don't have any point beyond this. Similarly, in the horizontal direction, I don't have any point beyond this.

So, when I am performing this iterative steps if I put a limit that I will not allow to grow the region beyond the horizontal and vertical dimensions of the original point set, then what I am going to get is a convex hull in true sense that is it will be minimal and of course, not only limiting the expansion beyond horizontal and vertical dimensions, if I expand if I limit the expansion in the diagonal directions as well; in the diagonal dimensions of the original point set, then what I will get is convex hull of the given set A in the true sense that is it will be minimal and at the same time, convex.

So, as we have said that convex hull is one of the very very important set, important concept which can be used for high level image understanding operation because we have said that the convex deficiency which is the difference between the convex hull of a given set and the given set. So, for a given set S if the convex hull is H, the set difference H minus S which tells you what is the convex deficiency. So, this convex deficiency is one of the very very important properties which can be utilized for high level image understanding operations. So, we will discuss about those high level image understanding operations in our subsequent lectures.

So now, today let us talk about another morphological operation, another morphological algorithm and we call it as thinning.

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So, as we have just said that this thinning is an operation which is useful to find out the skeleton of a given object shape and we have said earlier that this skeleton maintains the structure of the shape or the structural property of the shape and we can get an object descriptor, object description from the skeleton which can again be used for high level image interpretation or image understanding operation.

Now, let us see that how we can obtain the skeleton of a given shape of a given object shape by using the morphological operation. So here, the thinning operation is defined like this; see if I thin a given point set A with a structuring element say B; so this thinning operation is defined as A minus A again hit or mistransform with the structuring element B. So, this is what is by thinned image when it is thinned with the structuring element B and the same expression as you know from a set theory that it can be represented as A intersection with A hit or mistransform with B, take the complement of this.

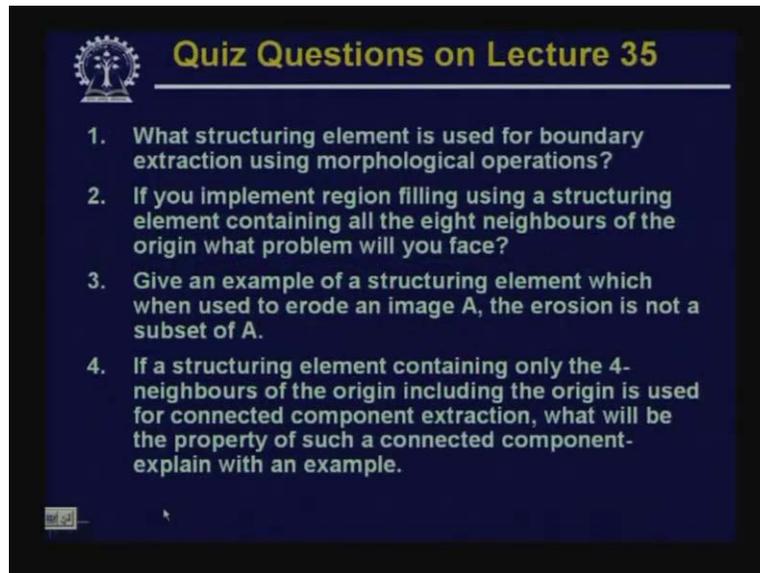
Again as before, instead of using a single structuring element, we use a set of structuring elements. So, we will assume that this structuring element B is a set of structuring elements which we say  $B^1, B^2, B^3$  upto say  $B^n$  where every structuring element  $B^i$  is nothing but a rotated version of structuring element  $B^{i-1}$ . Then, given the set of structuring elements  $B^1$  to  $B^n$ , the thinning of a given set A with the structuring element B and in this case, it is a set of structuring elements; so this is defined as first use thin set A with structuring element  $B^1$ , this result you thin with structuring element  $B^2$ , you continue like this and finally this output you thin with structuring element  $B^n$ . So, this completes one iterative step of the thinning operation.

So, for this given set of structuring elements  $B^1$  to  $B^n$ , we are doing successive thinning operations with different structuring elements present in our set and once you complete one particular iteration, you have to do this entire operation in a number of iterations until you reach convergence and in this particular case, the thinning with a particular structuring element in our set of structuring elements follows the same definitions that we have given here.

So, this entire operation that is thinning with all the structuring elements present in our set of structuring elements is done iteratively over a number of processes until and unless we reach the

convergence. So, we will continue with our discussion on this thinning operation as well as we will see some more morphological operations which are applicable in the image processing in our subsequent lectures. Now, let us see some of the quiz questions on today's lecture.

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So, the first question is what structuring element is used for boundary extraction using morphological operations? The second question, if you implement region filling with a structuring element containing all the eight neighbours of the origin, then what problem will you face? The third question, give an example of a structuring element which when used to erode an image A the erosion is not a subset of A. The fourth question, if a structuring element containing only the four neighbours of the origin including the origin is used for connected component extraction, then what will be the property of such a connected component? You have to explain with an example.

Thank you.