Modern Computer Vision

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Lecture-38

No, but then - 1 you are going to multiply the intensity. No. No, but that is not allowed in median it is an it is called an order statistics filter you can only order pixels you cannot you cannot multiply you cannot do averaging then it is like any other filter. So, it has to be with an order by ordering you have to get it not by any other means all right. So, let us go and talk about what is called edge detection what we have been doing I mean many of those things will now be useful for that and by the way when we say edge right it do not you know it does not necessarily mean that you know you are referring to a line or something edge could mean a pixel you know a place where there is a there is a drastic intensity variation and then right eventually you could probably you know club them all together in order to make some interpretations that you know there is a line here there is a curve there things like that. But right now it is not even clear as to when do I declare something is an edge pixel and so on right, but many of the things that we have done till now will now be handy and that is what we mean and you know when does an edge even okay first of all the applications right why would you even want to do an edge detection applications are many right.

One of the things that we already saw for example even in CNN filters when we saw we said that the initial filters represent something that the visual system does in the sense that right it actually picks up all the edges you have regions that are sensitive to orientation of edges and so on and then something else happens right along the way they get grouped and then there is some non-linear action on them and so on. So, we have already seen that that the low level features are important and typical low level features are edges. Then there are no then there are several real life examples where we know that somebody address just draws an edge map or somebody then we know that there is still so much information even in edges right you cannot say no to that right. I give you an image it does not mean that I have to shade every little part out there in order to convey something to you even without shading if I just gave you a contour of something right you will still be able to for example a table do I have to tell all the gray levels there to tell you that it is a table you do not need that right if I just draw the outline you tell it is a table right.

So, that way edges are very important I mean right and it is a matter of how you combine with them with maybe other information or whether you take them as a standalone and proceed that and all right we are not entering into you could be doing that also right. And then the other thing right that is the other thing right that you can ask is when does it arise right. So, when do you think that edges even arise when do you see edges I mean I mean you see you take an image right you see and possibly right looks like an edge right. So, when do you call that there is an edge well in the sense that what I am asking is that under what situations right can an edge arise physically when can it arise I mean if there is let us say a shadow perhaps right you will see an edge if there is a color texture change right in an image you see an edge right. So, it is an edge right does not kind of you know does not always mean that there has to be a discontinuity in depth without a discontinuity in depth also you can have edge variation if there is a discontinuity in depth very likely that you will have an edge there, but it does not automatically mean that it has to be there.

So, you can have various situations for example, right you can have I mean I think some examples are here itself which I can show for example, right here itself if you go by. Where is that full thing? So, if you see here right I mean yeah right I mean a definition is more or less like you know where there is a where is a significant change in intensity or transition. So, you can have an artist line drawing and then some of the things that I already talked about right. So, and of course, there are also other things you know using edges right you can actually you can trace what is called a vanishing point in an image and so on. This when we do single view geometry right we will come there because you have seen these railway tracks and already in an image it will appear like they are meeting somewhere in the image where actually where is in a real world we know that right they do not right, but in an image right they seem to meet.

So, the point right where they seem to meet is called the vanishing point and using that you can do certain things. So, that is again based upon edges right that we can actually try a track them then yeah right this is what I was telling. So, there is something called a normal this one a discontinuity surface normal a surface normal which basically means that you could have an object and then you know and then if the surface normal of the object suddenly changes because the shape of the object changes you can get you know a discontinuity you can get an edge. You can you know get an edge if there is a depth discontinuity that means there is totally like you are moving from one object to another something is behind something is in the front this is a different object that is a different object, but they are both coming in the same image you will again see an edge for example, what you are seeing here right this is like an edge you can get an edge I think now the color thing I do not know right that that seems to be missing here, but then yeah right you can also get you know if there is a texture or maybe even here I think you can see that here for example, right I mean you know that portion where there is a shadow right I mean there it looks like there is an there is an edge you can also have edges when there is a color change texture change so many right times when it when it arises. Now, let us just let us go back and kind of you know and then right let us just go back and talk about talk about some things right what we call.

So, this is so now two things that we typically use what is called a gradient edge gradient what is called an edge gradient. So, by which for example, right what we mean is you could have let us say an image g right which is let us say x y and and you know we can have a g x right which is supposed to be telling how does the intensity vary along as I move along the x direction right which is which is a gradient. So, right this you can think of dou g right with respect to dou x. So, this is like the change in intensity along this x direction then you can have something like g y right which is a gradient along y that is dou g by dou y right and typically right what we are actually interested in is actually the magnitude of of of the gradient. So, for example, right so so we can so the magnitude of of let us say gradient.

So, right let me just write this as magnitude of the gradient of g and that right I can write this as g x square + g y square root and there is something else which is like the right orientation. So, you can actually write something like you know a direction or you see right orientation orientation of the edge by which right what we actually mean is I will just write tell that in a minute. So, direction of the edge. So, this is like some c theta it is equal to you know inverse tan of g y by g x and what this actually means is this see for example, you know if we take our take our sort of you know convention to be this as increasing x that way and then y this way then what it means is right you could have. So, for example, right you know you could have an edge like this right where I have where I have 0 to see you know 255.

So, what this means is I have actually a vertical edge and then and then this this is see theta right it points in the direction of points in the direction of of the of the highest direction of the highest change in intensity change in you know intensity. So, for example, right in this case in this case you will have actually a theta which is actually 0 degrees because along along y right you do not have a you do not have a variation at all. So, it is like g y is 0 I mean because the edges right there is only a transition along x right as you move along y it is all 0 or it is all it is all 255. So, you have a g y which is 0 and then you have a g x right and and therefore, right theta is 0. So, if you change the if you change if you make it to be 255 0 then then it will mean that the edge goes in the other way.

So, if you make this as 255 and you make this as 0 then your then your see theta will be this which will be actually 100 and 180 conduction degrees and so on. So, so we have this notion of an orientation and you can also have inclined edges and so on it. So, you can think of a situation where you have an image and then and then right you have something like this and then let us say this is 0 and that is kind of say 255 and let us say in this case just for simplicity we can say that theta is probably 45 degrees or something. So, you have a g x component and then you have a g y component in the other upper two cases you had one of them is 0, but need not be. So, so you can have you can have something like this right where you have a theta you know which is kind of pointing in the in the kind of in the direction of the of the of the of the highest change of the same intensity right in this case it is going from 0 to say 255.

And we will see there are certain certain detectors right edge edge this one detectors that actually make use of this this information orientation information and most of them need the magnitude in any case, but there are some that may not need this, but they still go they still can can still function without them. But in general right when you whenever you talk about an edge pixel you are talking about the magnitude at that point right magnitude of the of the of the edge of the you know the strength of the edge. So, the so when we say gradient right magnitude of the gradient you are talking about relatively you are talking about the strength of that of that kind of pixel you are still at sort of a pixel level right we are still talking about what is happening at some x comma y. And then it remains to be seen right I mean you know how you then right what kind of higher inferences can you make if you had many of them and so on right. So, we are not yet there.

So, that is one thing right that I that I wanted to wanted to mention. So, so, so right. So, I think you can even talk this you know think of this as magnitude of g whichever way you want to write it and yeah this I said and and of course, you know. So, the filter right I mean I will be a little loose, but, but yeah, but then right you should remember that suppose I say that I say that right this is my filter let us say right I put this as - 1 - 1 - 1 0 0 0 1 1 1 it is one of the filters that you have already seen. And sometimes right people have what is called you know gain normalized filter and also they will have a scale factor here.

Let us not worry about worry about such simple things these are called you know gain normalized and so on, but that is just a matter of you know adding some scale factor there. But, but what you have to perhaps keep in mind is that we always mean theta right generally the sort of is a convention that we have is from 0 to 255 right we will want to think of that as theta equal to 0. So, if you use a filter like this right and if you are actually doing a convolution then you will flip it right and then and then and then right when you kind of flip it right then then this interpretation theta may turn out to be 180 right. So, you just make sure that that you kind of adhere to this. So, in this case it should perhaps be more meaningful to write it as 1 1 1 0 0 0 - 1 - 1 - 1.

So, that when you when you kind of flip it right one goes on the other side and therefore, right when you take the weighted average if 255 is on that side that will make it to be a positive number and therefore, your theta turns out to be 0 right that is all. So, that is something that is just a minor thing that you have to be worry about otherwise you might say I am getting a theta that is of the opposite sign or something right. Now, one of the things that we realize is that you know when you take a gradient typically we know that you know that also that also increases the amount of noise right because we know that gradient itself is a kind of a differentiation operation right. So, how much do you think a noise will go up by see for example, see if I had a case right where let us say let us say I have I have an image g m n which is what I observe ok, but then let us say this is some f m n at that. So, f m n is actually the ideal intensity that should have been there, but then right, but then right due to some noise I get some n of m comma n this is this is the noise right that is there and let us say this has some 0 mean.

So, this is again you know again a Gaussian ok. So, this is this is let us say Gaussian with 0 mean and let us say variance sigma square right that is what it is. So, this noise ok is actually Gaussian. So, now, if I take a difference operation if I do a difference operation on this g right then intuitively we feel that differentiation we always say will amplify noise will amplify noise this is something that we keep on saying right, but can we kind of tell as to how much will be the increase.

So, for example, right. So, if I do if you do something like g of m + 1 - g of ok. Now, let us just take right one one variable let us not let us have to get us a middle with both we can do that right there is no problem, but let us just take m - 1 and if I just if I just make it to be 1 d just let us just take a 1 d case right what will happen like f of m + 1 comma n + n of m + 1 comma n. So, a difference operation is this right that is what you will do a do a kind of a discrete approximation + sorry - then you have - f of m - 1 comma n - n of m - 1 comma n or in other words right we can think about this as f of m + 1 comma n - f of m - 1 comma n and then the noise component right. So, after the I mean right differentiation operation you have a new noise right which seems to. So, after that right this you can think of the output noise component that you have that has come out because of a differentiation operation right and therefore, if you if you compute the variance of this noise what will that be 2 sigma square right.

So, it will be actually 2 sigma square. So, it will it has 0 mean and of course, right this is all independent. So, therefore, right you get you get actually 2 sigma square that means, that means the fact is right if you take a first derivative right you are already blowing up the. So, the noise rate that is kind of see coming in is actually higher than the noise that you started off with that is the reason why we said that it is always a prudent thing to do first a smoothing right. So, that such small small variations that are over that are over that are there right they could be sort of mitigated to some extent and then and then and then right I mean and then you do a differentiation right.

So, the idea is to suppress noise with some kind of a smoothing operation and that may come at the expense of some loss of information right because you will when you smooth right it does not mean that it comes for free, but whatever it is right. So, smoothing for. So, that is why when you had a derivative of a Gaussian see dog there was there was another dog what was that. Difference. A difference of Gaussian yeah you saved my life.

So, right. So, it is like a difference of Gaussian the other one is a derivative of Gaussian right. So, these two are not the same a difference of Gaussian is supposed to be a good approximation to the log right that is what I had mentioned now in one of the classes, but derivative of a Gaussian it is also another way to way to take a difference to a difference operation where you first blur and then use a Gaussian and then and then you do you do you know a differencing operation. So, this is also another operator by the way right a dog this is a derivative of Gaussian. Now, let me let me just show you some examples right I mean where ok yeah yeah I mean let us just go back and kind of revisit the log the I mean Laplacian first right.

So, this. So, what we had right at that time we had talked about talked about a Laplacian a Laplacian was what you do dou square f by dou x square + dou square f by dou y square that was a Laplacian and the kernel was like 1 1 1 1 1 - 4 in the middle right north west east south and then - 4 in the middle. And so, so is a clearly that being a being a second derivative operator it will it will introduce right even more noise right, but suppose let us say let us say right let us kind of leave the noise aside we realize that yeah right it is going to be a problem because you know going for a second derivative will mean even more noise, but let us say right if you simply try it still doing something now now right I will just I will just give you an image and let us say right it has these intensities. So, just a just a toy example let us say that I have got 2 2 2 2 2 all 2s need not be like this no real image will look like this, but these are all toy example let us say I have got what is it 8 8 8 8 8 8 8 8 and all of these right will say here also it is 8 8 8 here on the left it is 2 2 2. Now, now suppose suppose I took this Laplacian right which is which is 4 in the middle and then what was it I mean do we have sin - 4 in the middle or 4 in the middle which which way which way did we 4 in the middle and then we had - 1 - 1 - 1 - 1 right 0s elsewhere right and therefore, if you apply this what will be the output. So, if you do a do a do a Laplacian kernel which means you will just do a do a convolution then what will you find of course, in this case it is simply it is a symmetric operator you flip it nothing happens what will be the output.

2 2 2 region it will all be 0s. It will all be 0s, but at the boundary right. So, so when I am here right what do you have I will have like 2 into 4 8 and then I have got like - 2 - 4 - 6 - 14. So, - 14 + 8 that is like - 6 right. So, let us say.

So, let us say right. So, you. So, you got like - 6 at at this place and then when you when you transition to 8 so it will be actually + 6. 0s elsewhere 0 elsewhere right. Now I said that I said that the Laplacian gives you a sense for 0 crossing right and then 0 crossing is a place where you can actually locate an edge. See the point is right when you when you talk about an edge it is not simply to identify the edge it is also important to have just one response for an edge. What it means is see for example, for example right I mean you know see here right I would like only only only as only a single sort of you know this one a response right.

I should not find a thick edge there because I see that there is only one edge and it is sharp right I mean I should not get multiple multiple kind of a response where I where I where I end up with actually a thick edge I am not saying it is happening here, but I am saying that is something that you do not want. You do what you also want is what is a localization a good localization that means I should know that the edge actually exists at that location. Now here where does the edge exist? Between the two so that means that the 0 crossing is happening somewhere between the left and the kind of say right pixel right. So, such a thing is called a sub pixel localization right because it is not happening at the place where you have where you have the intensity where you have a pixel location on your spatial grid right. So, it is happening like for example, you have one pixel here one pixel here and then right in between it is going through right or it is changing its sign the the second derivative and therefore, your actual edge is located somewhere here ok.

Now in this case right it is I mean I just took a toy example where it is - 6 and 6 right it is kind of an ideal case. If I had something like let us say what is it so suppose I said that right I had I have - 6 here and suppose I have 3 here suppose right the intensity is turned out to be like that where will the edge be? There I know somewhere in between because there has to it has crossed over but why and how but I want to know where ok. Now I know that it is not a straight forward answer. So, now what is typically done is you have to do some kind of some kind of an interpolation right. So, you have to do some kind of an interpolation to know, but if I said that the simplest I want to do is a kind of a linear interpolation.

Suppose I said I want to do a linear interpolation how would I do this now? Let us say simplest thing you can do right just take a linear interpolation and tell where the where the location where is the location now. 0 third. Where where it yeah it should be 2 thirds right. So, so suppose I say that right a a a is 0 ok and that is that is that location happens let us say right you know it is a delta away from let us say - 6 ok. Now now for example, right what is a now if I did a did a did a linear interpolation how would I write a in terms of - 6 and 3? I have to write a in terms of these two know.

So, how would I write it? I mean I am not even saying a is 0 now somewhere I want an I have an a somewhere I want to express it as you know in terms of - 6 and 3 right. We will then equate a to 0 because that is the 0 crossing, but in general let us put a somewhere and let us get a delta away from my. Delta is when delta is 0 it is - 6 and delta is. So, what should so I am just asking what is that expression then yeah you are telling me 1 - delta.

- 6. - 6. + delta into 3. + delta into 3 right delta times 3. + 9 delta -. So it is so it is what is this. So, a is - 6 + + 9 delta or 9 delta is 6 therefore, delta is 2 by 3 as he as he kind of rightly said and that also matches with what you said it will come to the closer to 3 because half is like in between right. So, it will come so it means that so actually right in reality you could do that I mean right.

So, when a people do this many times right when you want sub pixel accuracy or the simplest thing that you can do is you know you just go with some kind of you know some kind of you know this one a convention that that let us say if it is going from - 6 to 6 I will take - 6 to be my edge that is also possible, but you can also do sub pixel right where, but it will require more information, but right that is also commonly done. So, that is what we mean by pixel localization that means we have to know where exactly the edge is occurring. The problem with Laplacian right as we know the good thing is that it is telling you a 0 crossing right which means that there is actually very good information about where the where the edge lies and you can imagine right it is going to be very useful if you have actually a smooth transition like we showed the other day right you have a smooth transition if you take a kind of you know first derivative right then of course, you know that where the where the extrema is the you know that is an indication, but when you do when you take a when you take a second derivative the 0 crossing right automatically tells you right where it is, but then if you just took all the 0 crossings right that are there and if you declared all of them as edges right then it will it is not actually good idea because then you will have an image that just has you know too many things out there because you can have extraneous extrema and all right that will all enter.