

Modern Computer Vision

Prof. A.N. Rajagopalan

Department of Electrical Engineering

IIT Madras

Lecture-44

So, let us just look at a few examples, right and then try to understand how we can arrive at something called a response, a corner response function because we want to be able to flag a corner and this response function, right, the way we will actually devise it is such that it can even tell us whether it is a, whether it is an edge, whether it is a plane patch, you know, flat patch or whether it is a corner, right. But then before we go into that, let me just look at a few examples and let us try to plot how this I_x and I_y might actually look like, right. So suppose I have a case where let us say I just have some noise and this is like a uniform intensity + some A and I take a patch and suppose I try to plot I_x and I_y , okay. So what kind of values will I get for I_x and I_y ? Suppose I try to plot the gradient, so what it means is if I were to take this patch around, right, that was the idea, you know, last time when we talked about corner we said that we can take a patch and we have to move around wherever we are in the image. If you are near a corner then certain gradients will go up. If you are in a flat patch, what you would typically expect is that, right, this is because there is most of it is uniform and there is only probably the number of noise there.

So yeah, so the most of it is going to be 0 and perhaps we may just get some small gradients here and there but nothing, but nothing, right, that can be considered as significant. Then let us look at a case when we have an edge, a vertical edge let us say. Let us say we assume it to be 0 to 255, then correct, mostly, mostly 0 and you will have mostly I_x , right. So mostly I_x , so let us say it mostly, mostly that we have got some values of I_x and maybe read very few values of I_y , I mean it could be some small noise here and there, but more or less, right, it is going to be primarily dominated by I_x .

Why did I not put anything on the left side for I_x ? Intensity. Intensity, yeah, so 0 to 250, right, whichever way you do the patch you will always get an I_x that is positive, okay. Then good, that is a lot of alertness. Then we can have again a horizontal edge, right, let us forget that, that is probably easy you will get something along I_y . Then of course if I change the kernel then this will come on the opposite side, right.

Then let us first look at a case like this. I have a diagonal edge, let us say that I have got 0 to 255 and let us assume that, you know, going up is a positive gradient, that means if I had a vertical edge and 0 to 255 let us assume that that is all positive I_y and similarly, you

know, going from left to right is all positive I_x , okay. So if you have like this then what do you expect to see? I_x , I_y , no just one. Yeah, so if I take a patch here, right, I am going to move this patch around, right, then what kind of gradients will you see? I mean you are going to see both I_x and I_y , right, because there is a gradient along x , they will rely on some line, right. So you can imagine that they are kind of lying right along some sort of, you know, some line.

Now one of the things, right, that we actually that and then, okay, let us kind of look at a corner then finally, right. If I had a corner, right, something like this and so let us say, right, there is 0 inside the corner and 255 outside or whichever, let us always assume that we are just looking at the positive gradients then now what will happen is you will have actually whichever way you move, okay, you will get actually gradients because it is a corner and therefore it you can think of, okay, let me put it in different colors, so you can think of a lot of activity all around, I mean, whichever way you move there is going to be a lot of activity because you are sitting at a corner and these are not very small, I mean these are unlike the ones that we showed for a flat patch where also, right, because of noise maybe you had some gradient but by here these are going to be significant and these will be whichever way you go, right, you will get actually gradients. Now when you see something like this, right, you see that, you know, so for example, if I go here, right, just you are going to motivate the notion of corner response function and I know just to motivate, right, what the r can do. So last time we said that r was like P diagonal P transpose and we said that the eigenvectors of r are the columns of P , so everything is actually 2×2 , this is just that gradient matrix, right. So we said that this guy will have λ_1 , so this one, diagonal is this λ_1 , 0 , 0 , λ_2 , again values are all actually greater than or equal to 0 in this case, that gradient already we saw last time and then the point is the eigenvectors, right, which are the columns of P .

Now whenever you talk about doing a compression, right, what do you do, I mean if I had a data where let us say some data, right, does not have to be I_x and I_y , if I had a data that had a correlation like this where it looks like x and y sort of move together, right, when x increases looks like y will also increase or it can be a negative correlation, in this case it is positive. So you always think about a way by which you can actually de-correlate the data, right, because it looks like it is unnecessary to send both, I mean if you are looking at transmitting something right, it looks like transmitting one is as good as telling something about the other, so why transmit both, right, so at that time what do you do, this is what we teach in a PCA. So we say that look at the, you know, so kind of compute the covariance of that data and then compute the eigenvectors and the eigenvectors will then point towards, so the highest most significant eigenvector which has of course highest eigenvalue, it points towards the maximum variance and then you can, you will have an orthogonal eigenvector to that which will point towards the next highest dominant sort of

a direction then whatever, you know, it is a 2 cross 2 that is all you have, but imagine, right, I mean if you had a higher dimensional space and then you can think of all these eigenvectors pointing in say different directions and here for us it is simply the gradient, right, so it is a variance of this, of the gradient because that is where, that is what r has, right, that is what r is about and therefore, right, it is clear that if I try to, so for example, right, I mean if I did a PCA, right, I mean suppose, I mean which is exactly this, so I have got the eigenvectors, right, so in this case, right, how do you think for example, right, for this, so how do you think will my kind of eigenvectors look like, how do you think is my eigenvector going to look like, so it is going to look like this, right, so along this, yeah, along this guy, right, I will have the maximum spread, right and as you see that is orthogonal to the edge, right and then you will have another direction which will be in this case perpendicular but then that may have very little variance, okay, maybe I should just show it like you know, very little variance there in that direction and therefore, right, you get a sense for something is going on, right, if you are setting an edge, be it inclined or be it vertical or horizontal, whatever it is, right, you will get a sense for what might be happening there and as far as a corner is concerned, right, you expect both eigenvalues to be reasonably significant because there is a spread along x and there is also, also you know, a good spread, I mean, so whichever way you see, right, there is, I mean whichever way you move there is actually, you know, say significant amount of variation and therefore, right, here, so what you have, so what you can think about is, so for example, right, if you have this case then you can sort of say that both λ_1 and λ_2 are going to be very small because the spread itself is very small. If you have something like this, right, where you have an edge, whether it is inclined or whatever you can say that one of them, right, no, λ_1 perhaps is high but then λ_2 is going to be low, that is in this case, right, you are going to say that both of them are have to be low and in this case you expect both of them to be high, I mean high in the sense that not like, not like those small little values that you might see if it was just a plain batch, right, this is exactly what is exploited by this corner response function as it is called by Harris, this Harris detector and that corner response function as it is or corner response or it is also called the corner strength, okay. Now, the way, right, this is set up is that you know, you can get a feel for in fact all three of them, okay, is given by, is given by some m is equal to $\lambda_1 \lambda_2 - \text{some } \kappa \text{ times } \lambda_1 + \lambda_2 \text{ square}$.

Now, if you had a flat patch, okay, and this κ is typically like in the range, you know, 0.04 to such a small number, okay, 0.06, again this is some something that let us say people have arrived at, okay, so that is the range of this κ . So, if you have a flat patch then you know that λ_1 and λ_2 are both small, right, are both small and therefore, what do you expect this m to be like, close to 0, right. So, your response will be such that m is approximately 0.

So, m is approximately 0, right. So, if it is a flat patch and that is one way to know where

you are, then another is edge. So, in edge, right, so you have λ_1 high and we will always assume that λ_1 the highest eigenvalue, you have ordered it, right and λ_2 is low and whenever you say λ_2 that means orthogonal to the edge direction that is the eigenvector, you know. So, in this case, so in this case, right, what do you think, what do you think m will be like. So, so you see, so what you have is κ for edge, so $\lambda_1 + \lambda_2$, right, so you have λ_1 high and you have like λ_1^2 square and then you have got $\lambda_1 \lambda_2$, this λ_2 is low, right, so λ_1 into λ_2 will get kind of say pulled down, right, because this λ_2 is low and therefore, you will get actually m to be less than 0 because even though κ is low, but then $\lambda_1 \lambda_2$ is going to be really low and therefore, this will be typically m less than 0, I mean significantly less than 0 because this is also we are saying approximately 0, but this will be significantly less than 0 and if you had a corner, then both λ_1 and λ_2 being significant, when we say that high, right, what we mean is they are both going to be significant and therefore, what will happen is, you know, even though $\lambda_1 + \lambda_2$ might be reasonable, but then this κ will pull it down, but $\lambda_1 \lambda_2$ are both reasonably high, therefore, we believe that m is, m will be significantly greater than 0, if it is a corner, right.

So, so something like this is what will flag as you kind of move the patch around the image, right, so everywhere, I mean you can get a sense for the how the gradients are and based upon that, if you, if you computed a corner response, then you would know right which one of these actually could be potential corners. Of course, one of the things right that you still need to do is what is called, so what you do is, you know, you typically set a threshold because you know, you cannot, you cannot just declare, right, everything is a corner just because m cross is 0. So, what you normally do is, you set a threshold, set a threshold, again there are some hyper parameters right and, and, and only points with corners, with corner strength, let me write it as C as corner strength, greater than this threshold, whatever, set a threshold T , greater than T , okay and find, okay, we are still not, not actually declaring them as corners, okay and find all points, all the points with let us say a corner strength greater than T and then what do you think after this you would want to do based upon whatever you have learnt till now. I have, I mean this was a similar problem that we encountered sometime earlier, right, I set a threshold but then right there are so many guys that will rear their heads now because it is, you have to, no, so how would you, how would you handle this, something that we did very recently, I had even mentioned at that time that, non-maxima suppression, right, that is what you do, so it is like saying that now we want to identify local maxima, right, because there are so many of them that could be, that could, like I said that could potentially flag themselves as candidates, therefore you do what is called, so on these points, right, so perform non-maxima suppression because this could lead to too many, too many corners, corners as possibilities, so use non-maximum suppression or non-maxima suppression, so this NMS rate is something that you will hear again and again, okay, it is a simple idea but you know it is needed. And this again, net people around a 3 by 3 neighborhood, so what do you do,

so you take a 3 by 3 neighborhood is chosen around a potential corner that means something that has crossed this threshold around a potential corner and it is retained if it is a, if it is a, if it is a local maximum, retained if it is a local maximum and also they have some other conditions also, they say that it should be at least 1% of the maximum strength of a corner in the image and so on, these are some add-ons, right, which you can keep putting, so it is like saying that just because it is a local maximum and just because it has crossed the threshold necessarily, so I think just one more safeguard that you know it should be at least 1% of the maximum strength of the corner that you would find in the entire image, right, that is okay, not so, it is irrelevant.

Okay, now one other thing, right, that we also talked about when we did edges, right, when we did edge points and all, there was one more thing that we were worried about of course, now we are talking about corners but now what is it, so for example, right, in an image now I have been and you see actually when you use this thing, right, on an image, it is kind of, it is kind of very interesting to see how it, you know, what all it flags and so on and there are different people, right, depicted in various ways, some people actually put a square around that and you may think that why is it flagging the whole area, right, when it is actually a corner but then it is a way of showing, right, so what they mean is more the strength of the corner, the larger the square around the area of the square around which, so the center of the square is actually the point but then how do you indicate the strength of the corner, right, so for that they will actually put a box and the area of the box corresponding to the, corresponds to the strength of the corner, right, so you should not think that they are probably flagging a whole area as a corner or something, so that is just a, you know, a depiction part, how let us say, different people depict but the simplest way to depict is to actually show it as a point, okay, on the image and one more thing, right, so for example, okay, now if I actually did this, let us say, right, and I found these corners, right, and then as you also asked, right, it is not like they have to be orthogonal edges and so on, okay, you can have various situations where something gets flagged as a corner, so I see this is all like, you know, let us also accept that, right, this is like a theory that we can lay down for the, for the situation which is actually easy to understand, right, but then the moment you apply it on the algorithm then all these cases, right, I mean, you know, so wherever, wherever, right, it believes that there is significant, you know, change in, you know, in I_x and I_y , significant variation it will start flagging, okay, so what we are deriving is for an understanding sake, right, because this is what we can understand easily but then when we actually put it on the image, right, sometimes you may, you may even, you know, it may not be even clear to you as to why something got flagged as a corner but maybe you should go and examine what the response was, so I am saying it is not so clean, I mean, see what I am drawing is something this is like, you know, it is like a cleanest thing which you can, which you can visualize, right, but the moment you apply it on an image, right, it will flag everywhere and then, you know, you may wonder what is going

on but yeah, but then it is doing what it is supposed to do. One more thing, right, so when I say that this is a corner, what else can I do? Again, let us go back to what we did before, is there something else that we should worry about? What else, I mean, so for example, right in edge point what were the even 3 things that we were actually worried about? Single response, okay, that we have here because we have done NMS and we have got one response, what else? Single response, then there was, what else was there? Localization, right, so here do not you think that we might have to do some kind of a sub pixel localization because we are thinking that that is where the corner is but it is possible that the actual maximum is occurring somewhere around it, right, within a pixel, right, that is called, that is what we mean by sub pixel, right. So Harris detection is typically done up to sub pixel accuracy, okay, sub pixel localization as it is called.