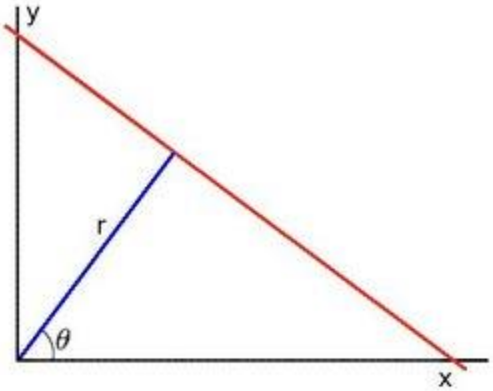
Concepts Important for Lane Detection M1

Hough Line Transform

1. As you know, a line in the image space can be expressed with two variables. For example:

    a. In the **Cartesian coordinate system:** Parameters: (m, b).

    b. In the **Polar coordinate system:** Parameters: (r, θ)



For Hough Transforms, we will express lines in the *Polar system*. Hence, a line equation can be written as:

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right)$$

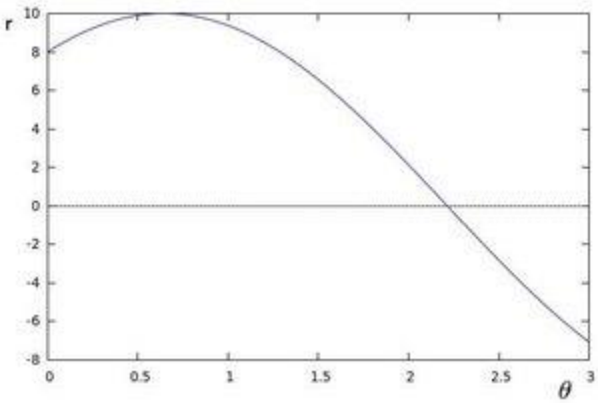
Arranging the terms: $r = x\cos\theta + y\sin\theta$

1. In general for each point (x_0, y_0), we can define the family of lines that goes through that point as:

$$r_\theta = x_0 \cdot \cos\theta + y_0 \cdot \sin\theta$$

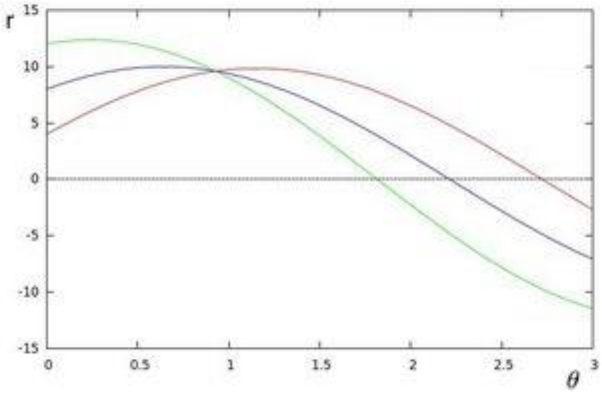
Meaning that each pair (r_θ, θ) represents each line that passes by (x_0, y_0).

2. If for a given (x_0, y_0) we plot the family of lines that goes through it, we get a sinusoid. For instance, for $x_0 = 8$ and $y_0 = 6$ we get the following plot (in a plane θ - r):



We consider only points such that $r > 0$ and $0 < \theta < 2\pi$.

3. We can do the same operation above for all the points in an image. If the curves of two different points intersect in the plane θ - r, that means that both points belong to a same line. For instance, following with the example above and drawing the plot for two more points: $x_1 = 4$, $y_1 = 9$ and $x_2 = 12$, $y_2 = 3$, we get:

   The three plots intersect in one single point $(0.925, 9.6)$, these coordinates are the parameters (θ, r) or the line in which (x_0, y_0), (x_1, y_1) and (x_2, y_2) lay.

4. What does all the stuff above mean? It means that in general, a line can be *detected* by finding the number of intersections between curves.The more curves intersecting means that the line represented by that intersection have more points. In general, we can define a *threshold* of the minimum number of intersections needed to *detect* a line.

5. This is what the Hough Line Transform does. It keeps track of the intersection between curves of every point in the image. If the number of intersections is above some *threshold*, then it declares it as a line with the parameters (θ, r_θ) of the intersection point.

For further reference Visit:

1. https://www.youtube.com/watch?v=4zHbI-fFIlI
2. https://www.youtube.com/watch?v=G019Av7XhGo

Canny Edge Detection

Canny Edge Detection is a popular edge detection algorithm. It was developed by John F. Canny in

1. It is a multi-stage algorithm and we will go through each stages.
2. **Noise Reduction**

   Since edge detection is susceptible to noise in the image, first step is to remove the noise in the image with a 5x5 Gaussian filter. We have already seen this in previous chapters.

3. **Finding Intensity Gradient of the Image**

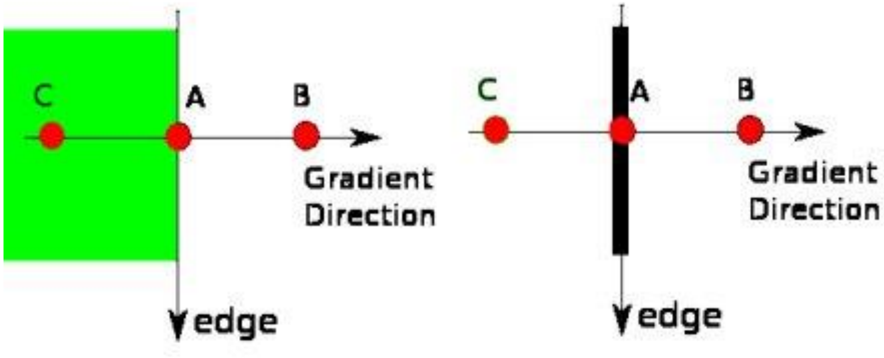
   Smoothened image is then filtered with a Sobel kernel in both horizontal and vertical direction to get first derivative in horizontal direction (G_x) and vertical direction (G_y). From these two images, we can find edge gradient and direction for each pixel as follows:

   $$Edge\_Gradient(G)=G_{2x}+G_{2y}−−−−−−−\sqrt{}Angle(\theta)=\tan_{-1}(G_yG_x)$$

   Gradient direction is always perpendicular to edges. It is rounded to one of four angles representing vertical, horizontal and two diagonal directions.

4. **Non-maximum Suppression**

   After getting gradient magnitude and direction, a full scan of image is done to remove any unwanted pixels which may not constitute the edge. For this, at every pixel, pixel is checked if it is a local maximum in its neighborhood in the direction of gradient. Check the image below:



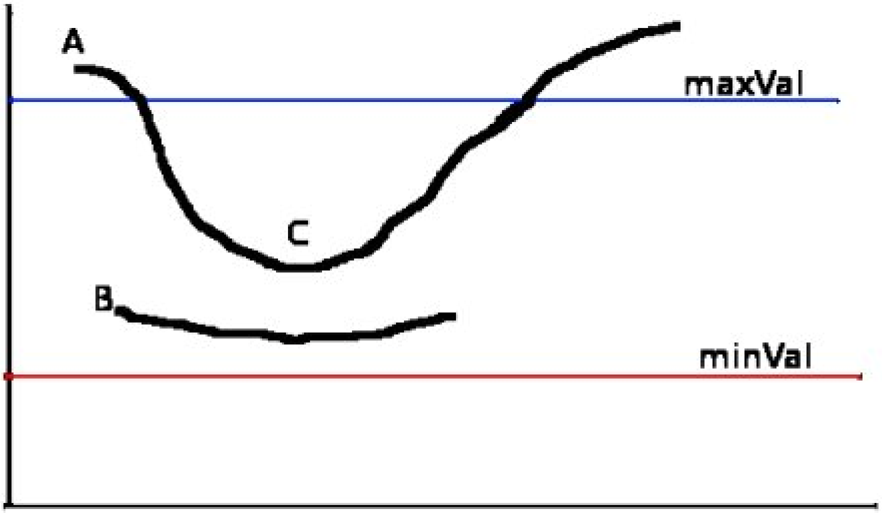
image

Point A is on the edge (in vertical direction). Gradient direction is normal to the edge. Point B and C are in gradient directions. So point A is checked with point B and C to see if it forms a local maximum. If so, it is considered for next stage, otherwise, it is suppressed (put to zero).

In short, the result you get is a binary image with "thin edges".

5. **Hysteresis Thresholding**

This stage decides which are all edges are really edges and which are not. For this, we need two threshold values, minVal and maxVal. Any edges with intensity gradient more than maxVal are sure to be edges and those below minVal are sure to be non-edges, so discarded. Those who lie between these two thresholds are classified edges or non-edges based on their connectivity. If they are connected to "sure-edge" pixels, they are considered to be part of edges. Otherwise, they are also discarded. See the image below:



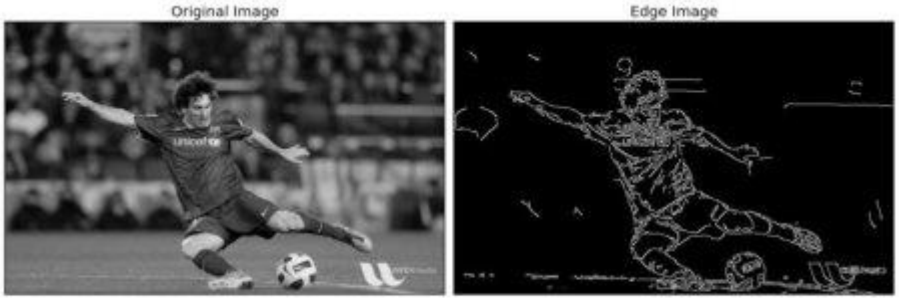
image

The edge A is above the maxVal, so considered as "sure-edge". Although edge C is below maxVal, it is connected to edge A, so that also considered as valid edge and we get that full curve. But edge B, although it is above minVal and is in same region as that of edge C, it is not connected to any "sure-edge", so that is discarded. So it is very important that we have to select minVal and maxVal accordingly to get the correct result.

This stage also removes small pixels noises on the assumption that edges are long lines.

So what we finally get is strong edges in the image.

See the result below:



image

For further reference Visit:

1. https://www.youtube.com/watch?v=sRFM5IEqR2w
2. https://www.youtube.com/watch?v=3nMrLfDopfM

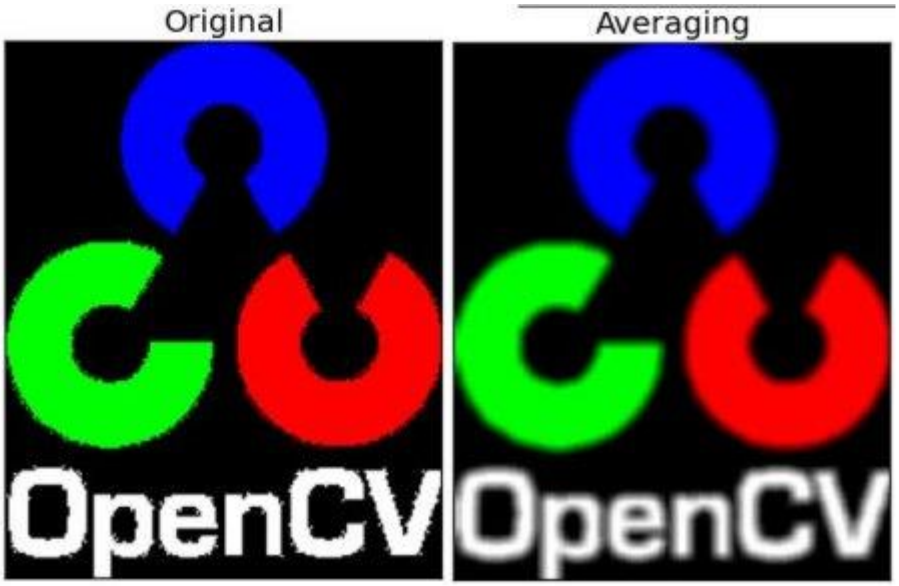
Smoothing Images

As in one-dimensional signals, images also can be filtered with various low-pass filters(LPF), high-pass filters(HPF) etc. LPF helps in removing noises, blurring the images etc. HPF filters helps in finding edges in the images.

OpenCV provides a function **cv2.filter2D()** to convolve a kernel with an image. As an example, we will try an averaging filter on an image. A 5x5 averaging filter kernel will look like below:

$$K = \frac{1}{25} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Operation is like this: keep this kernel above a pixel, add all the 25 pixels below this kernel, take its average and replace the central pixel with the new average value. It continues this operation for all the pixels in the image.



image

Image Blurring (Image Smoothing)

Image blurring is achieved by convolving the image with a low-pass filter kernel. It is useful for removing noises. It actually removes high frequency content (eg: noise, edges) from the image. So edges are blurred a little bit in this operation. (Well, there are blurring techniques which doesn't blur the edges too). OpenCV provides mainly four types of blurring techniques.

1. Averaging

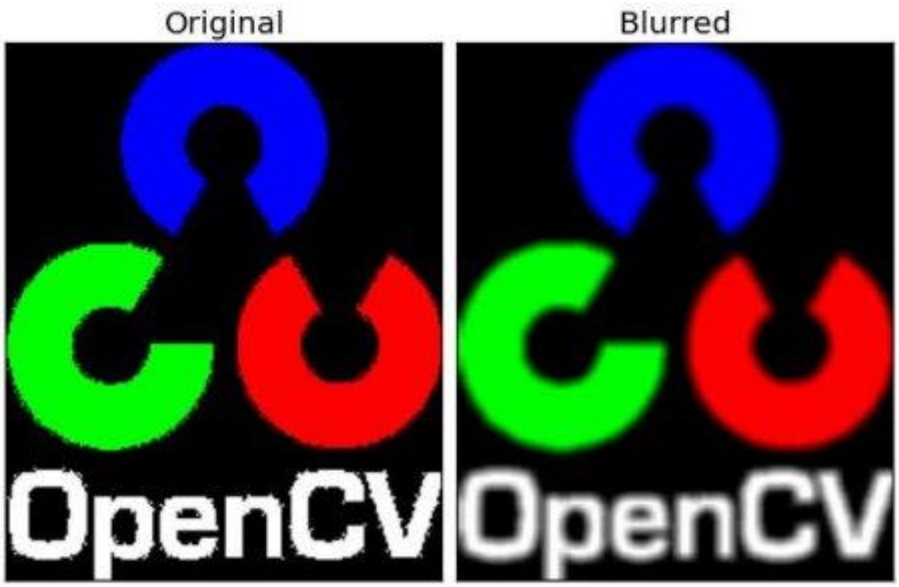
This is done by convolving image with a normalized box filter. It simply takes the average of all the pixels under kernel area and replace the central element. This is done by the function **cv2.blur()** or **cv2.boxFilter()**. Check the docs for more details about the kernel. We should specify the width and height of kernel. A 3x3 normalized box filter would look like below:

$$K=19[[|111111111]]|$$

Note

> If you don't want to use normalized box filter, use **cv2.boxFilter()**. Pass an argument normalize=False to the function.

Result:



image

2. Gaussian Blurring

In this, instead of box filter, gaussian kernel is used. It is done with the function, **cv2.GaussianBlur()**. We should specify the width and height of kernel which should be positive and odd. We also should specify the standard deviation in X and Y direction, sigmaX and sigmaY respectively. If only sigmaX is specified, sigmaY is taken as same as sigmaX. If both are given as zeros, they are calculated from kernel size. Gaussian blurring is highly effective in removing gaussian noise from the image.

If you want, you can create a Gaussian kernel with the function, **cv2.getGaussianKernel()**.

Result:

Original
Blurred

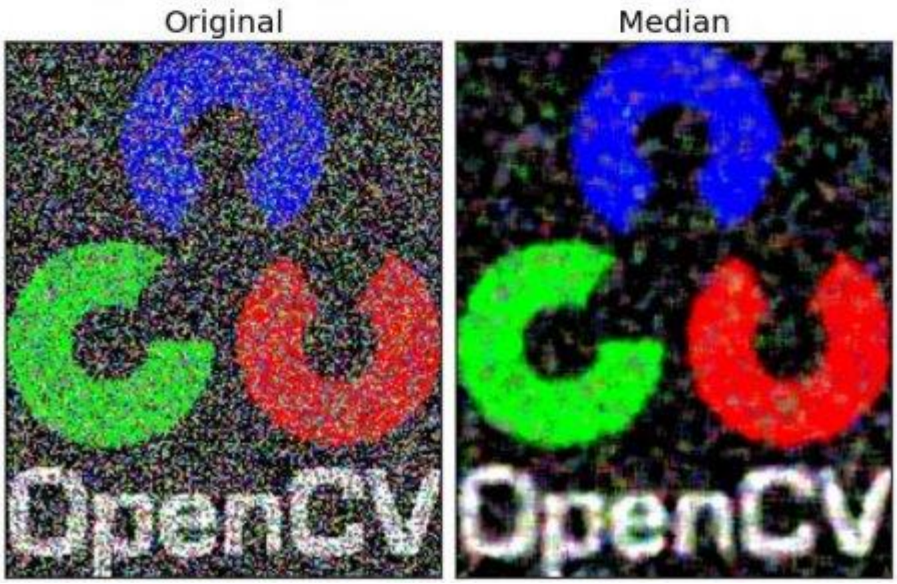
image

3. Median Blurring

Here, the function **cv2.medianBlur()** takes median of all the pixels under kernel area and central element is replaced with this median value. This is highly effective against salt-and-pepper noise in the images. Interesting thing is that, in the above filters, central element is a newly calculated value which may be a pixel value in the image or a new value. But in median blurring, central element is always replaced by some pixel value in the image. It reduces the noise effectively. Its kernel size should be a positive odd integer.

In this demo, I added a 50% noise to our original image and applied median blur. Check the result:

Result:



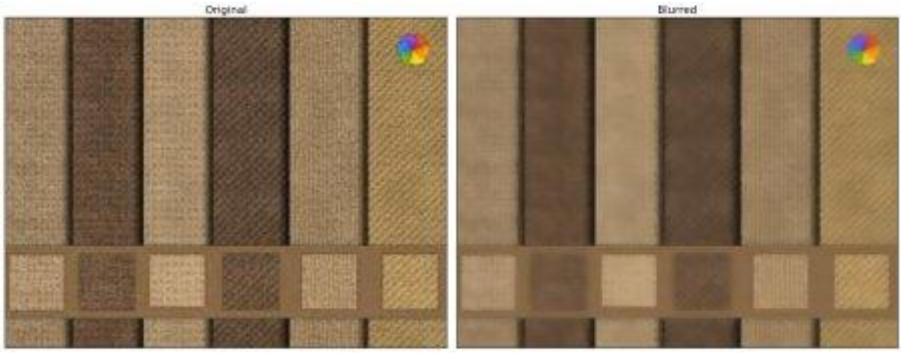
image

4. Bilateral Filtering

cv2.bilateralFilter() is highly effective in noise removal while keeping edges sharp. But the operation is slower compared to other filters. We already saw that gaussian filter takes the a neighbourhood around the pixel and find its gaussian weighted average. This gaussian filter is a function of space alone, that is, nearby pixels are considered while filtering. It doesn't consider whether pixels have almost same intensity. It doesn't consider whether pixel is an edge pixel or not. So it blurs the edges also, which we don't want to do.

Bilateral filter also takes a gaussian filter in space, but one more gaussian filter which is a function of pixel difference. Gaussian function of space make sure only nearby pixels are considered for blurring while gaussian function of intensity difference make sure only those pixels with similar intensity to central pixel is considered for blurring. So it preserves the edges since pixels at edges will have large intensity variation.

Result:



image

See, the texture on the surface is gone, but edges are still preserved.