# Computer Vision and Deep Learning

Ch 04



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#### Edge Detection

Edge Detection: 윤곽선을 검출하는 기술로써, 영상에서 객체의 경계를 찾기 위한 기법

Edge Operator: 이미지에서 Edge Position, magnitude, orientation을 추출하는데 활용된다.

#### Three performance criteria in Canny Edge Detection

#### 1. Good Detection

Edge point의 marking 실패율을 낮출수록 좋다. (SNR을 올릴수록 좋음)

#### 2. Good Localization

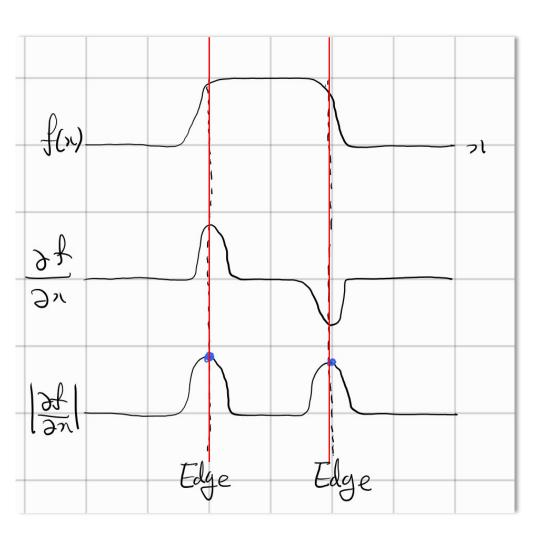
Edge로 판단한 지점과 실제 Edge의 중심이 가까울 수록 좋다.

#### 3. Only one response to a single Edge

Edge에 대해 단 하나의 응답을 해야 한다. (NMS 적용)



### 1D Edge Detection



#### $Gradient(\nabla)$

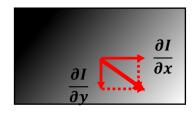
- 1. Edge의 크기와 방향, 위치를 얻어낼 수 있다.
- 2. Edge 검출에 용이한 Threshold를 찾아야 한다.
- 3. Convolution을 두 번 수행한다. x축, y축
- 4. non-linear operatior이다. 각 픽셀에 대한 미분 값이 픽셀 값 자체에 의존하기 때문



### 2D Edge Detection



$$\nabla I = \left[\frac{\partial I}{\partial x}, 0\right]$$



$$\nabla I = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right]$$

#### **Gradient Magnitude**

$$S = \|\nabla I\| = \sqrt{(\frac{\partial I}{\partial x})^2 + (\frac{\partial I}{\partial y})^2}$$

#### **Gradient Orientation**

$$\theta = \tan^{-1}(\frac{\partial I}{\partial x} / \frac{\partial I}{\partial y})$$

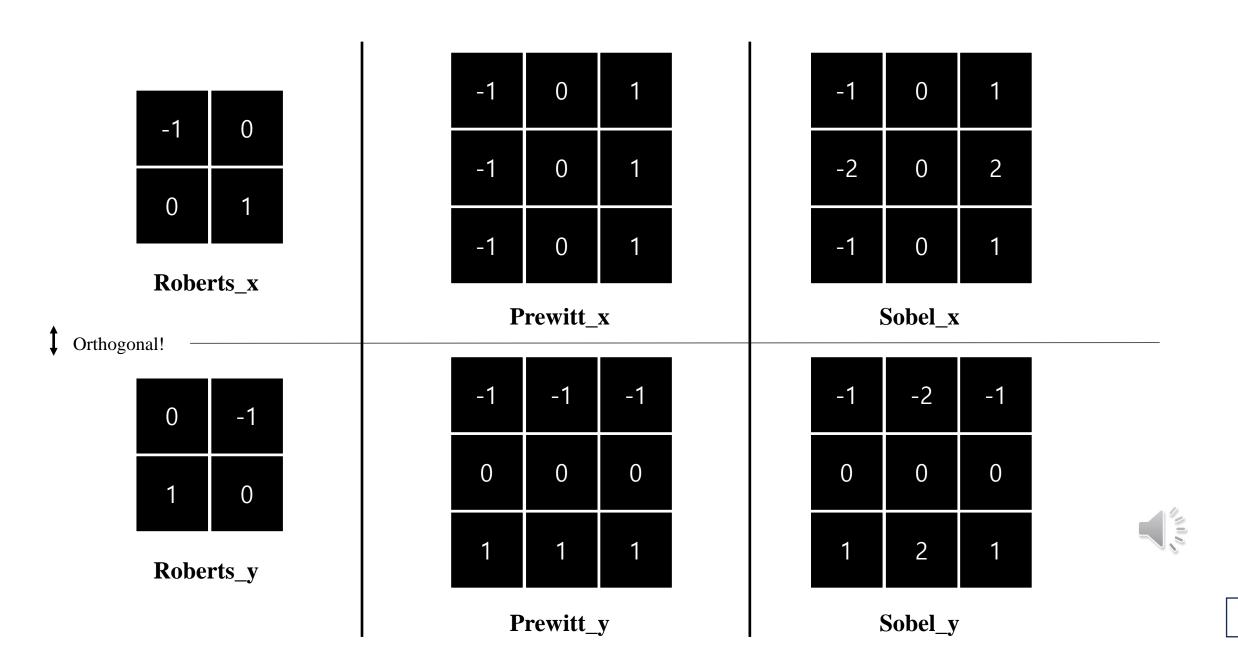


### Discrete Gradient(**∇**) Operator

$$f'(n) = \begin{cases} \int_{2\pi/2}^{2\pi/2} \frac{f(n) - f(n)}{2\pi/2} & \text{in } \frac{f(n) - f(n)}{2\pi/2} \\ \int_{2\pi/2}^{2\pi/2} \frac{f(n)}{2\pi/2} & \text{in } \frac{f(n) - f(n)}{2\pi/2} \\ = \int_{2\pi/2}^{2\pi/2} \frac{f(n) - f(n)}{2\pi/2} + \frac{f(n) - f(n)}{2\pi/2} \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n-1)}{2\pi/2} \right) \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} \right) \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} \right) \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} \right) \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)}{2\pi/2} \right) \\ = \frac{1}{2} \left( \frac{f(n+1)}{2\pi/2} - \frac{f(n+1)$$



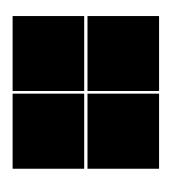
### Discrete Gradient(**∇**) Operator



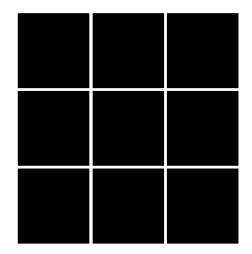
## Discrete Gradient(**∇**) Operator

#### Filter size

Good Localization
Noise Sensitive
Poor Detection

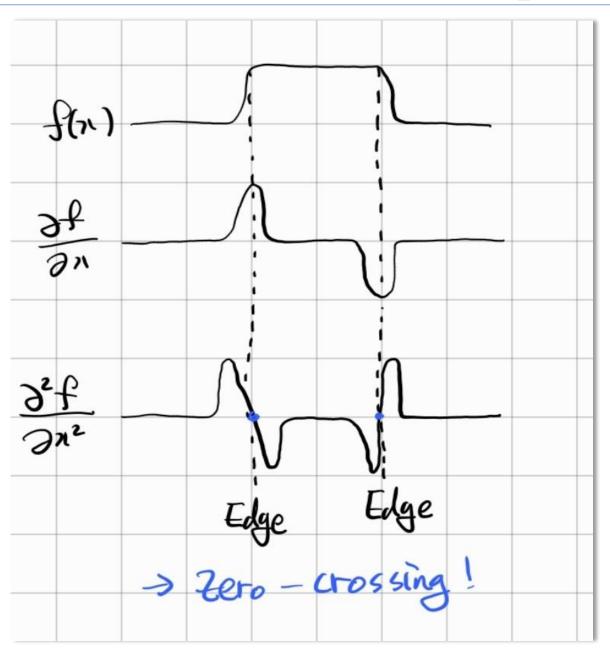


Poor Localization Less Noise Sensitive Good Detection





## Discrete Laplacian ( $\nabla^2$ ) Operator



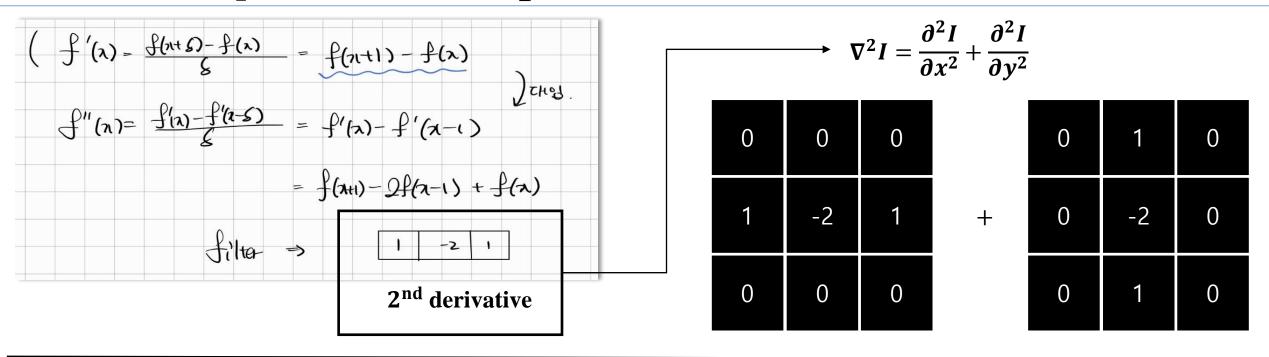
Laplacian( $\nabla^2$ )

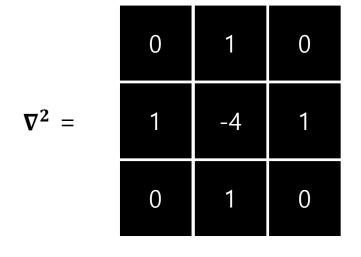
- 1. Edge의 위치를 얻어낼 수 있다.
- **2. Zero-Crossing** 모든 기울기의 합이 0이다.
- 3. Convolution을 한 번 수행한다.
- 4. Linear-operator이다.

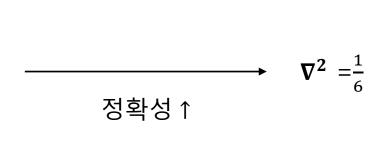
Laplacian은 주변 픽셀에 대한 합으로 나타낼 수 있고, 이 합의 계수는 고정된 상수이기 때문



## Discrete Laplacian $(\nabla^2)$ Operator

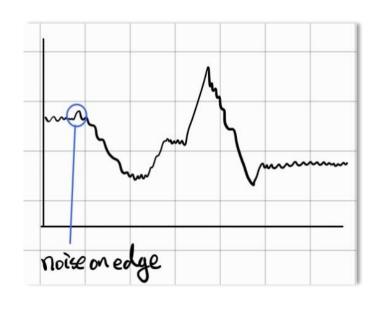






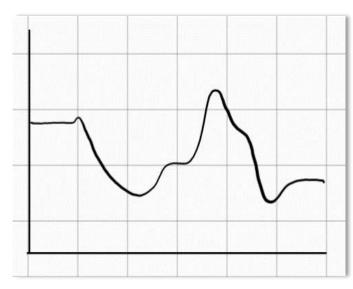
1	4	1	
4	-20	4	
1	4	1	

### Operator Application



f

Noise때문에 어디서든 **기울기가 빠르게 변화**한다.

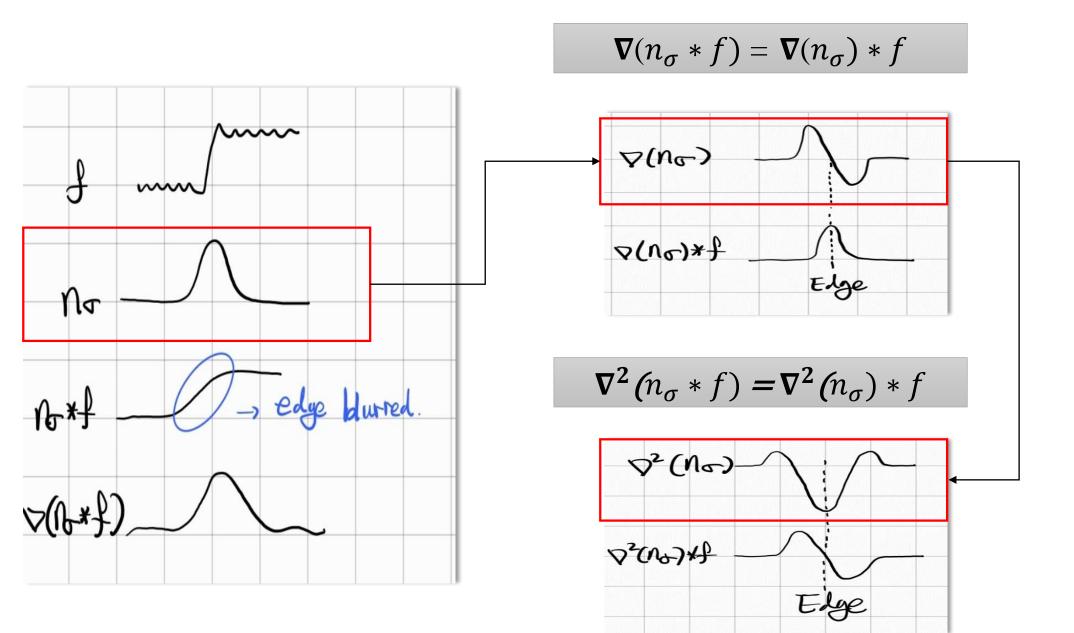


 $n_{\sigma} * f$ 

**가우시안 스무딩**을 통해 노이즈 완화



#### Operator Application





#### **Canny Edge Detector**

최소 오류율, 위치 정확도, 한 두께라는 기준에 따라 목적 함수를 정의한 에지 검출 최적화 기법

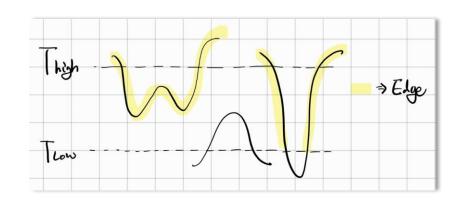
#### **Non-Maximum Suppression**

한 두께 에지를 출력하기 위한 기법이다. 에지 방향에 수직인 두 이웃 화소의 에지보다 크면 에지로 살아남고, 그렇지 않으면 억제한다.

#### Hysteresis thresholding

 $\|\nabla I(x,y)\| < T_{Low}$ : not Edge  $\|\nabla I(x,y)\| > T_{high}$ : Edge

Then,  $T_{Low} < ||\nabla I(x, y)|| < T_{high}$  ?





#### **Algorithm**

1. 
$$n_{\sigma} * I$$
  
2D Gaussian 필터를 이용하여 이미지를 **스무딩**

2. 
$$\nabla n_{\sigma} * \mathbf{I}$$
 Sobel 연산자를 이용하여 Gradient를 구한다.

Gradient magnitude : 
$$\|\nabla n_{\sigma} * \mathbf{I}\|$$
  
Gradient orientation :  $\widehat{n} = \frac{\nabla n_{\sigma} * \mathbf{I}}{\|\nabla n_{\sigma} * \mathbf{I}\|}$ 

## **3. Non-maximum suppression** 두꺼운 에지 제거

**4. Hysteresis thresholding**  
최종 에지 선정 (
$$T_{high}$$
는  $T_{low}$ 의 2~3배 설정)



#### Step 1.

2D Gaussian 필터를 이용하여 이미지를 **스무딩** $(n_{\sigma}*I)$ 

```
Mat Gaussian Kernel(int size, float sigma) {
  Mat kernel(size, size, CV_32F);
  int kernelCenter = (size - 1) / 2;
  float sum = 0.0;
  for (int i = 0; i < size; i++) {
    for (int j = 0; j < size; j++) {
       int x = kernelCenter - i;
       int v = kernelCenter - i:
      kernel.at < float > (i, j) = exp(-(static_cast < float > (x * x) +
         static_cast<float>(y * y)) / (2.0 * sigma * sigma)) / sqrt(2.0 * PI * sigma * sigma);
       sum += kernel.at<float>(i, j);
  kernel /= sum;
  return kernel;
```



Gaussian filter  $\sigma = 1$ , size = 3x3

Step 2. Sobel 연산자를 이용하여 Gradient를 구한다.

```
Gradient magnitude : \|\nabla n_{\sigma} * \mathbf{I}\|
Gradient orientation : \widehat{n} = \frac{\nabla n_{\sigma^*} \mathbf{I}}{\|\nabla n_{\sigma^*} \mathbf{I}\|}
```

```
Mat Sobel_operator(int x) {
  Mat sobelKernelX = (Mat_{<float>(3, 3) << -1, 0, 1, -2, 0, 2, -1, 0, 1)}
  Mat sobelKernelY = (Mat_{<float>(3, 3) << -1, -2, -1, 0, 0, 0, 1, 2, 1)};
  if (x == 1) return sobelKernelX;
  else return sobelKernelY;
           Sobel x
          Sobel_y
```

```
img_{w.at} < float > (y, x) = img_{x.at} < float > (y, x) * weight + img_{y.at} < float > (y, x) * (1 - weight);
Sobel combined
                                             return img_w;
                        for (int x = 0; x < img_x.cols; ++x) {
                          for (int y = 0; y < img_y.rows; ++y) {
```

Gradient<sup>O</sup> 크기와 방향 계산

```
|Mat calc _gradient_magnitude_orientation(Mat&img_x, Mat&img_y, int k) {
  Mat mag = Mat::zeros(img_x.rows, img_x.cols, CV_32F);
  Mat orient = Mat::zeros(img x.rows, img x.cols, CV 32F);
      mag.at < float > (y, x) = sqrt(img_x.at < float > (y, x) * img_x.at < float > (y, x) + img_y.at < float > (y, x) * img_y.at < float > (y, x));
      float a = 10*atan2(img_v.at < float>(v, x), img_v.at < float>(v, x));
      if (a < o) a = -a:
      orient.at<float>(y, x) =a;
  if (k == 1) return mag;
  else return orient:
```

∃Mat weight\_x\_y(Mat& img\_x, Mat& img\_y, float weight) {

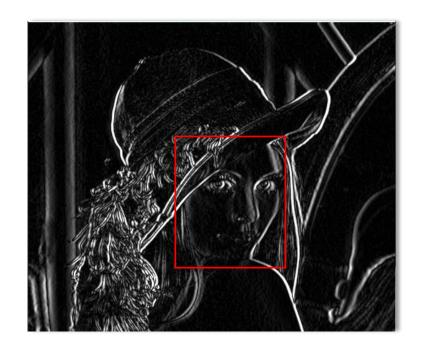
for (int x = 0;  $x < img_x.cols$ ; ++x) { for (int y = o;  $y < img_y.rows$ ; ++y) {

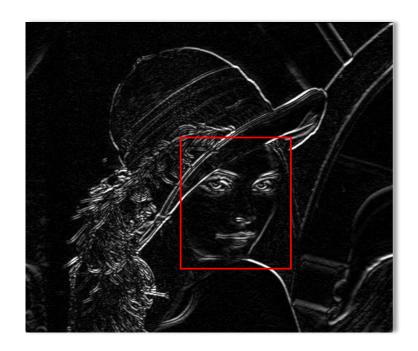
Mat img\_w = Mat::zeros(img\_x.rows, img\_x.cols, CV\_32F);

Step 2. Sobel 연산자를 이용하여 Gradient를 구한다.

Gradient **magnitude** :  $\|\nabla n_{\sigma} * \mathbf{I}\|$ 

Gradient **orientation** :  $\widehat{n} = \frac{\nabla n_{\sigma^*} \mathbf{I}}{\|\nabla n_{\sigma^*} \mathbf{I}\|}$ 





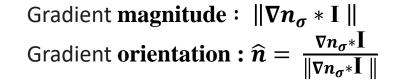


 $Sobel\_x\_conv$ 

 $Sobel\_y\_conv$ 

Sobel\_combined w = 0.5

Step 2.Sobel 연산자를 이용하여 Gradient를 구한다.





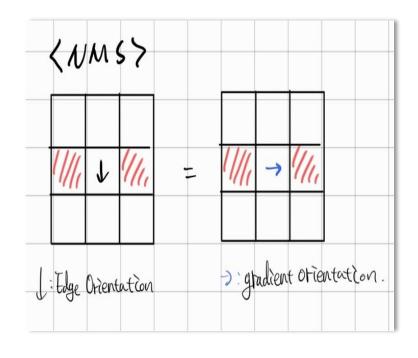
**Gradient magnitude** 



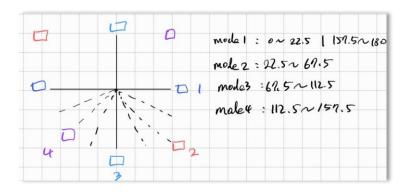
**Gradient orientation** 

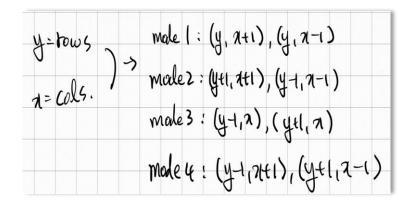


Step 3.
Non-maximum suppression 두꺼운 에지 제거



**Criteria: Gradient orientation** 





- 1. Atan2 -> - $\pi$  ~  $\pi$
- 2. 각도의 절댓값 저장( 0 ~ 180°)
- 3. 각도에 따른 모드 설정
- 4. 모드에 따른 주변 픽셀 고려 후 억제



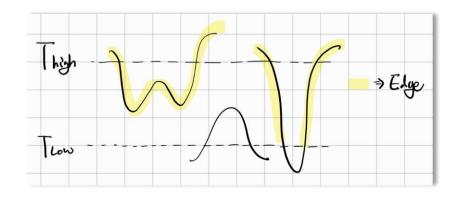
Step 3.
Non-maximum suppression 두꺼운 에지 제거



Img\_NMS

```
Mat NMS(Mat& mag, Mat& orient) {
  Mat img_NMS(mag.rows, mag.cols, CV_32F);
  Mat mag_p;
  int d = 1;
  int mode = o;
  copyMakeBorder(mag, mag_p, d, d, d, d, BORDER_CONSTANT, o);
  for (int x = d; x < mag_p.cols - d; ++x) {
   for (int y = d; y < mag_p.rows - d; ++y) {
      float value = orient.at<float>(y-d, x-d);
      if ((0 <= value && value < 22.5) || (157.5 <= value && value < 180)) mode = 1;
      else if (22.5 <= value && value < 67.5) mode = 2;
      else if (67.5 <= value && value < 112.5) mode = 3;
      else mode = 4;
      switch (mode) {
      case 1:
        if ((mag_p,at<float>(y, x) < mag_p,at<float>(y, x + 1))) img_NMS.at<float>(y - d, x - d) = o;
        else img NMS.at<float>(y - d, x - d) = mag p.at<float>(y, x);
        break:
        if ((mag_p.at < float)(y, x) < mag_p.at < float)(y + 1, x + 1)) || (mag_p.at < float)(y, x) < mag_p.at < float)(y - 1, x - 1))) img_NMS.at < float)(y - d, x - d) = 0;
        else img_NMS.at<float>(y - d, x - d) = mag_p.at<float>(y, x);
        break:
        if ((mag_p,at < float)(y,x) < mag_p,at < float)(y-1,x)) | (mag_p,at < float)(y,x) < mag_p,at < float)(y+1,x))) img_NMS,at < float)(y-d,x-d) = 0;
        else img_NMS.at<float>(y - d, x - d) = mag_p.at<float>(y, x);
        break;
       case 4:
        if ((mag_p,at < float > (y,x) < mag_p,at < float > (y-1,x+1)) \mid (mag_p,at < float > (y,x) < mag_p,at < float > (y+1,x-1))) img_NMS,at < float > (y-d,x-d) = 0;
        else img NMS.at<float>(y - d, x - d) = mag p.at<float>(y, x);
         break;
   return img_NMS;
```

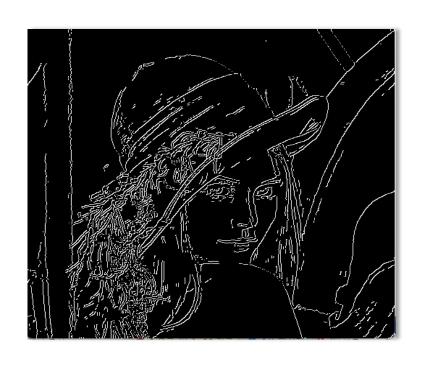
Step 4.
Hysteresis thresholding 최종 에지 선정 ( $T_{high}$ 는  $T_{low}$ 의 2~3배 설정)



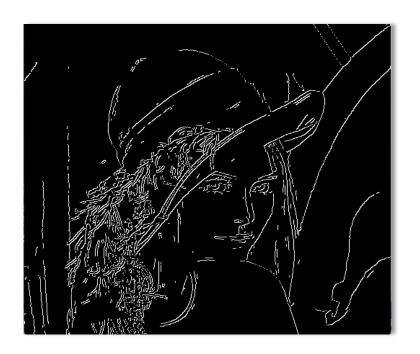
```
T_{Low} < \|\nabla I(x,y)\| < T_{high}
\|\nabla I(x,y)\| > T_{high}: Edge \|\nabla I(x,y)\| < T_{Low}: not Edge
```

```
Mat Hysteresis_Threshold(Mat&img_NMS, float lowThreshold, float highThreshold) {
  Mat img_H = Mat::zeros(img_NMS.rows, img_NMS.cols, CV_8U); int d = 1;
  Mat img_NMS_p; copyMakeBorder(img_NMS, img_NMS_p, d, d, d, BORDER_CONSTANT, o);
  int flag = o;
  for (int x = d; x < img_NMS_p.cols -d; ++x) {
    for (int y = d; y < img_NMS_p.rows - d; ++y) {
      if (img_NMS_p.at<float>(y, x) > highThreshold) { img_H.at<uchar>(y - d, x - d) = 255; }
      else if (img_NMS_p.at<float>(y, x) >= lowThreshold) {
         for (int m = -1; m <= 1; ++m) {
          for (int n = -1; n <= 1; ++n) {
            if (img_NMS_p.at<float>(y + m, x + n) >= highThreshold) {
               flag = true;
               break;
           if (flag) break;
         img_H.at < uchar > (y - d, x - d) = (flag) ? 255 : o;
    else \{img_H.at < uchar > (y - d, x - d) = o;\}
    flag = o;
  return img_H;
```

Step 4. Hysteresis thresholding 최종 에지 선정



lowThreshold = 30HighThreshold = 60



lowThreshold = 30 HighThreshold = 90



 $\begin{aligned} &lowThreshold = 50 \\ &HighThreshold = 150 \end{aligned}$ 

# 감사합니다.

