assignment05

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Mathematical Foundations for Computer Vision and Machine Learning
*** Assignment05 - Computation of Image Features using Convolution ***
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Link to Github

1 Setting up

Input image is read to the program by `io.imread` having `0-255` value for each pixels.

```
In [1]: import matplotlib.pyplot as plt
        import numpy as np
        from scipy import signal
        from skimage import io, color
        from skimage import exposure
        import sys

        file_image          = 'cau.jpg'

        im_color           = io.imread(file_image) # 0-255
        im_gray            = color.rgb2gray(im_color) # 0-1
```

2 Visualize input image for color/gray

Image can be shown by `plt.imshow()` . The `cmap` attribute indicates the colormap of the picture. There are lots of selections in colormap.
Colormap in matplotlib

```
In [2]: # Print input image
        plt.title('color image')
        plt.imshow(im_color)
        plt.axis('off')
        plt.show()
        plt.title('gray image')
        plt.imshow(im_gray, cmap='gray')
        plt.axis('off')
        plt.show()
```

color image

gray image

3 Define Essential Functions

I define some funtions that is essential to implement this program.

3.1 Definition of Derivative

In this assignment, derivative of the image is defined as

$$f'(x) = \frac{f(x+1) - f(x)}{1 - 0}$$

`compute_x_derivation` defines the convolution kernel for computing the derivative in x-direction and executes convolution process.

`compute_y_derivation` defines the convolution kernel for computing the derivative in y-direction and executes convolution process.

3.2 Definition of Gradient Magnitude

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

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

`compute_magnitude_grad` is a function for computing the magnitude of the gradient.

3.3 Definition of Gradient Direction

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

`compute_grad_direction` is a function for computing the direction of the gradient. It uses arctan to find theta.

`smoothing` defines smoothing kernel which is called Gaussian smoothing filter and does smoothing process.

`own` defines my own kernel which is sharpening filter and does sharpening process.

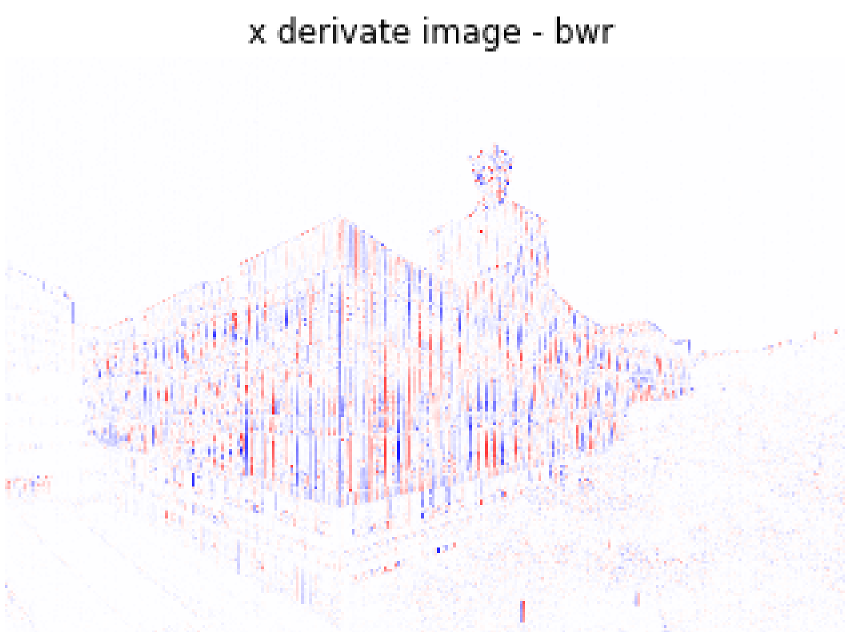
In [3]:
```
def compute_x_derivation(im):
    ker_deri_x = np.array([[0, 0, 0], [0, -1, 1], [0, 0, 0]])
    return signal.convolve2d(im, ker_deri_x, boundary='symm', mode='same')

def compute_y_derivation(im):
    ker_deri_y = np.array([[0, 0, 0], [0, -1, 0], [0, 1, 0]])
    return signal.convolve2d(im, ker_deri_y, boundary='symm', mode='same')

def compute_magnitude_grad(grad_im):     # absolute value of gradient
    return np.sqrt(np.sum(np.power(grad_im,2),axis=0))

def compute_grad_direction(grad_im):     # direction of gradient
    return np.arctan(np.divide(grad_im[1],grad_im[0]+sys.float_info.epsilon))
```

```
def smoothing(im):  # smoothing kernel - Gaussian smoothing filter
    smoothing_kernel = np.divide(np.array([[1,2,1],[2,4,2],[1,2,1]]),16.)
    return signal.convolve2d(im, smoothing_kernel, boundary='symm', mode='same')

def own(im):    #own kernel - increase contrast (sharpening)
    own_kernel = np.array([[-1,-1,-1],[-1,9,-1],[-1,-1,-1]])
    return signal.convolve2d(im, own_kernel, boundary='symm', mode='same')
```

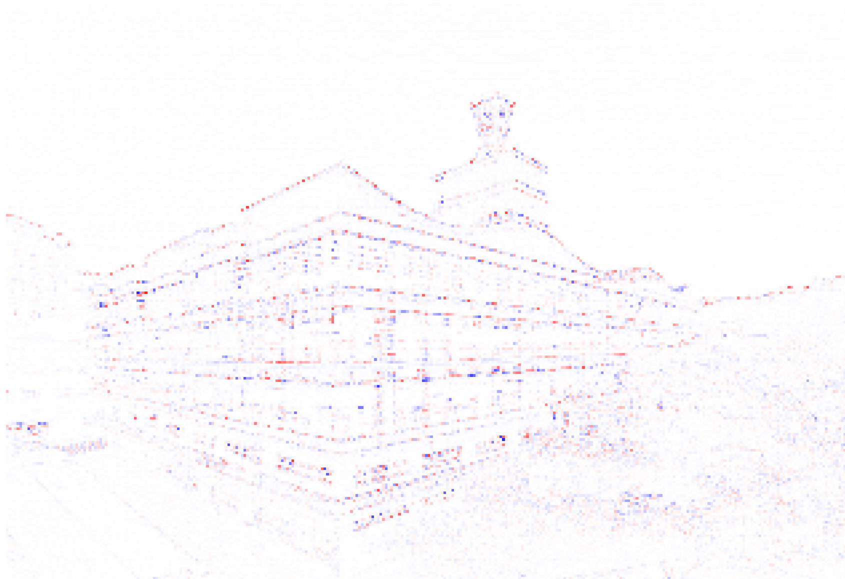
4 Plot Derivative in X-Direction, Y-Direction

Since there can be negative value, I used diverging colormap.

```
In [4]: # Define colormap
        cmap = 'bwr'  # Diverging Colormap: blue - white - red

        # Derivative filter results
        dim_dx        = compute_x_derivation(im_gray)
        dim_dy        = compute_y_derivation(im_gray)

        plt.title('x derivate image - '+cmap)
        plt.imshow(dim_dx, cmap=cmap)
        plt.axis('off')
        plt.show()
        plt.title('y derivate image - '+cmap)
        plt.imshow(dim_dy, cmap=cmap)
        plt.axis('off')
        plt.show()
```



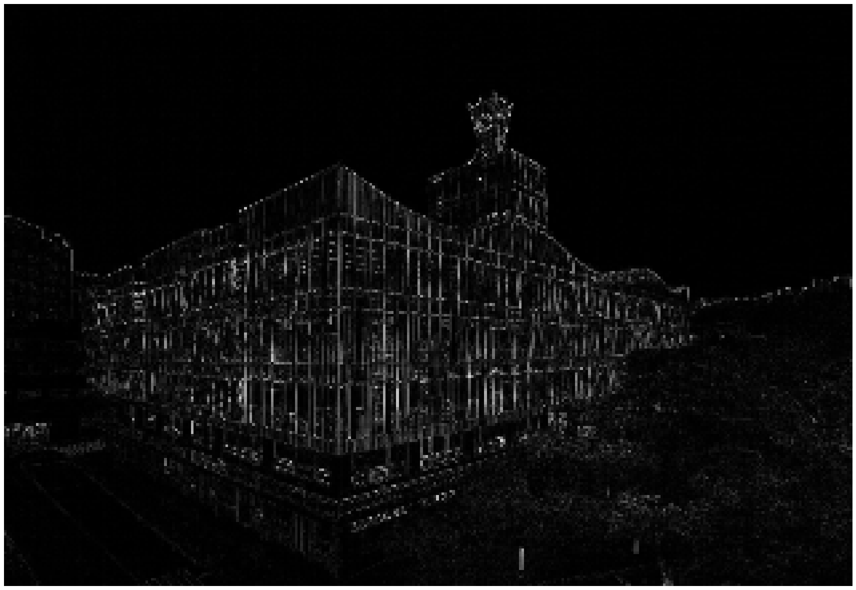
y derivate image - bwr



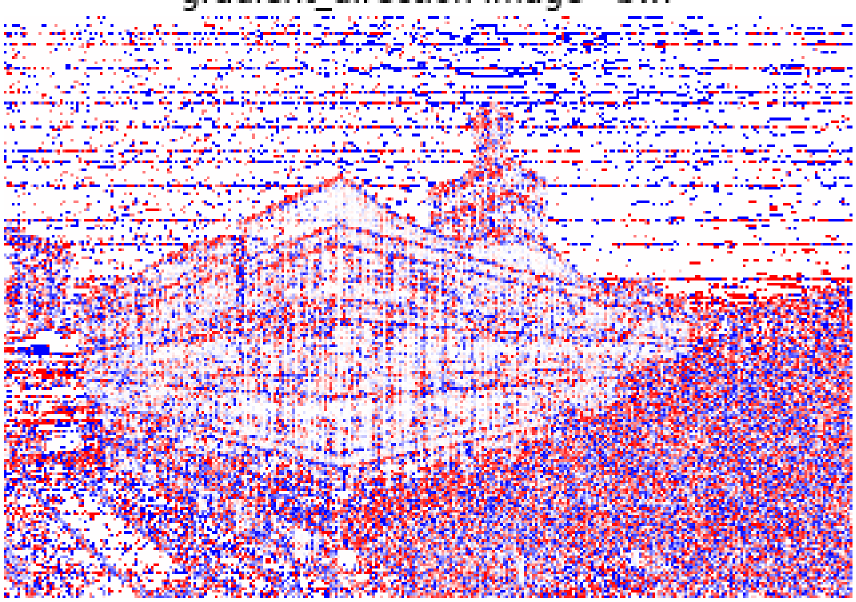
5 Plot Absolute Value of Gradient and Direction of Gradient

In [5]:
```
# Image Gradient
grad_im = np.array([dim_dx, dim_dy])

# absolute value of gradient
gradient_magnitude = compute_magnitude_grad(grad_im)
plt.title('gradient_magnitude image - gray')
plt.imshow(gradient_magnitude, cmap='gray')
plt.axis('off')
plt.show()

# direction of gradient
gradient_direction = compute_grad_direction(grad_im)
plt.title('gradient_direction image - '+cmap)
plt.imshow(gradient_direction, cmap=cmap)
plt.axis('off')
plt.show()
```

gradient_magnitude image - gray



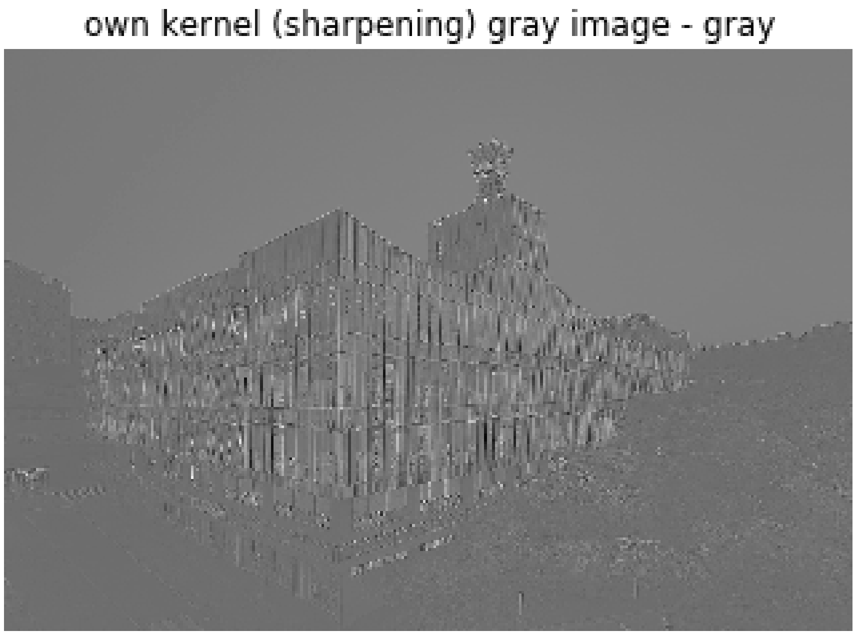
gradient_direction image - bwr



6 Result Image with smoothing kernel and own kernel

In [6]:
```
# smoothing kernel
smoothed = smoothing(im_gray)
plt.title('gaussian smoothing gray image - '+'gray')
plt.imshow(smoothed, cmap='gray')
plt.axis('off')
plt.show()


# own kernel
own_image = own(im_gray)
plt.title('own kernel (sharpening) gray image - '+'gray')
plt.imshow(own_image, cmap='gray')
plt.axis('off')
plt.show()
```

gaussian smoothing gray image - gray



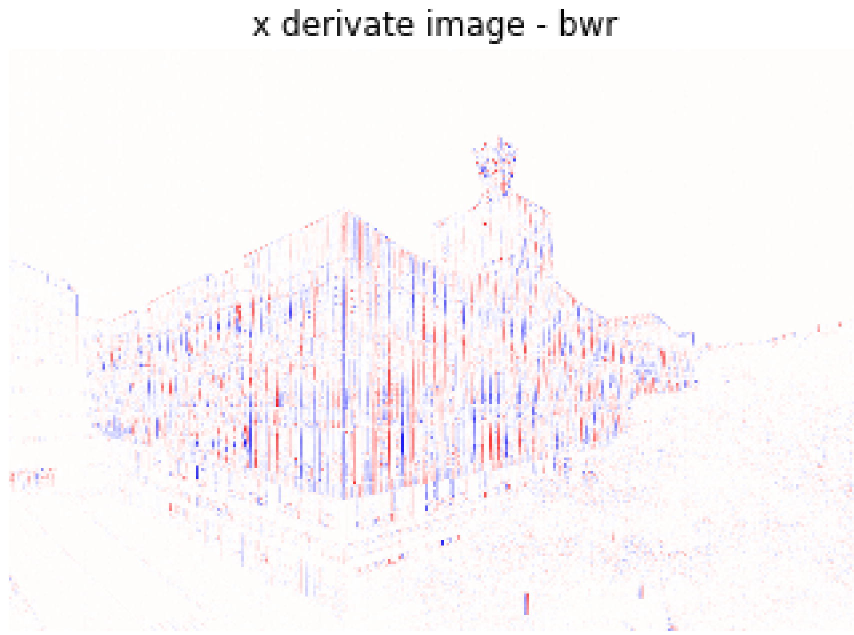
7 Now It's COLOR image

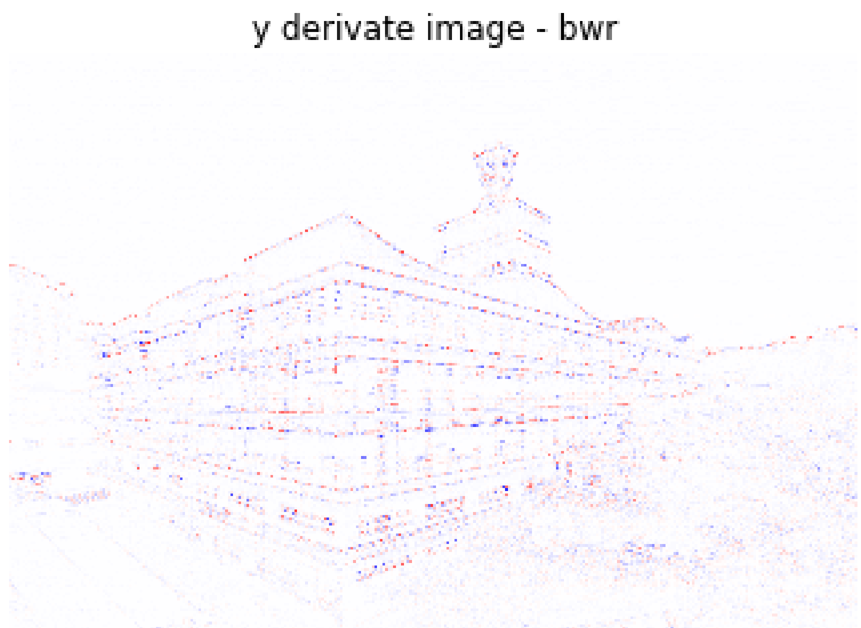
Color image is made of 3 channels.

```
In [7]: # derivate for color image (3ch)
        cr_dim_dx = np.array(im_color,dtype="float64")
        cr_dim_dy = np.array(im_color,dtype="float64")
        new_im = np.divide(im_color,255.0)
        for i in range(3):
            cr_dim_dx[:,:,i] = compute_x_derivation(new_im[:,:,i])
            cr_dim_dy[:,:,i] = compute_y_derivation(new_im[:,:,i])
            plt.title('x derivate image - ' + cmap)
            plt.imshow(cr_dim_dx[:,:,i], cmap=cmap)
            plt.axis('off')
            plt.show()
            plt.title('y derivate image - ' + cmap)
            plt.imshow(cr_dim_dy[:,:,i], cmap=cmap)
            plt.axis('off')
            plt.show()
```

x derivate image - bwr

y derivate image - bwr


x derivate image - bwr


y derivate image - bwr

x derivate image - bwr

y derivate image - bwr

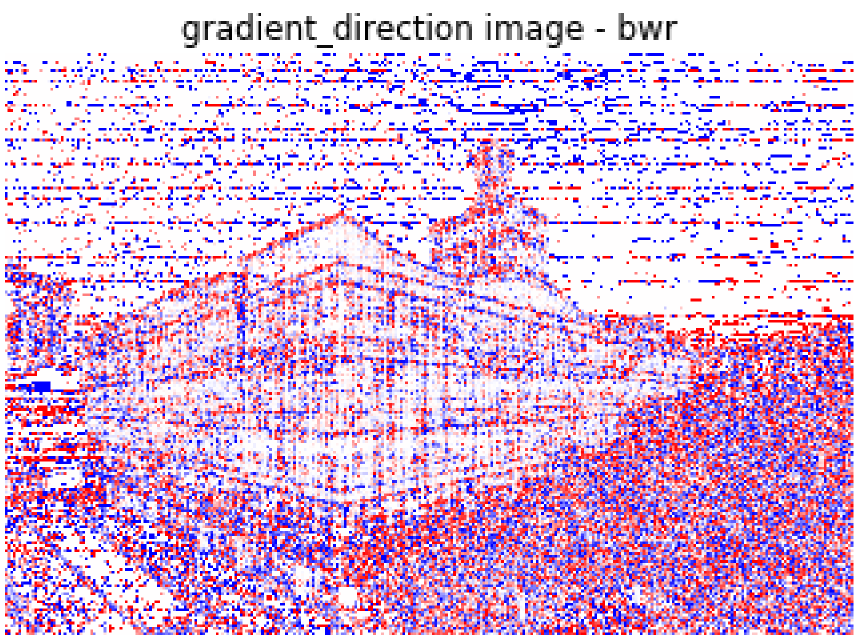
8 3ch Gradient Direction - Average

In [8]:
```
# Image Gradient (3ch)
cr_grad_im = np.array([cr_dim_dx, cr_dim_dy])

# absolute value of gradient (3ch)
gradient_magnitude = compute_magnitude_grad(cr_grad_im[:,:,:,0])
plt.title('gradient_magnitude image - red')
plt.imshow(gradient_magnitude, cmap='Reds')
plt.axis('off')
plt.show()
gradient_magnitude = compute_magnitude_grad(cr_grad_im[:,:,:,1])
plt.title('gradient_magnitude image - green')
plt.imshow(gradient_magnitude, cmap='Greens')
plt.axis('off')
plt.show()
gradient_magnitude = compute_magnitude_grad(cr_grad_im[:,:,:,2])
plt.title('gradient_magnitude image - blue')
plt.imshow(gradient_magnitude, cmap='Blues')
plt.axis('off')
plt.show()

# direction of gradient 3ch -> average -> 1ch
grad_im = np.average(cr_grad_im,axis=3)
gradient_direction = compute_grad_direction(grad_im)
plt.title('gradient_direction image - '+cmap)
plt.imshow(gradient_direction, cmap=cmap)
plt.axis('off')
plt.show()
```

gradient_magnitude image - red

gradient_magnitude image - green


gradient_magnitude image - blue


gradient_direction image - bwr

9 Define new functions for color images

In [9]:
```
# Define new functions for color images
def smoothing_3ch(im):
    smoothing_kernel = np.divide(np.array([[1, 2, 1], [2, 4, 2], [1, 2, 1]]), 16.)
    result = im
    for i in range(3):
        result[:, :, i] = signal.convolve2d(im[:, :, i], smoothing_kernel, boundary='sym
    return result

def own_3ch(im):
    own_kernel = np.array([[-1, -1, -1], [-1, 9, -1], [-1, -1, -1]])
    result = im
    for i in range(3):
        result[:, :, i] = signal.convolve2d(im[:, :, i], own_kernel, boundary='symm', mo
    return result
```

10 3ch Smoothing and Sharpening

In [10]:
```
# smoothing kernel (3ch)
smoothed = smoothing_3ch(im_color)
plt.title('gaussian smoothing gray image - '+'color')
plt.imshow(smoothed)
plt.axis('off')
plt.show()


# own kernel
own_image = own_3ch(im_color)
plt.title('own kernel (sharpening) gray image - '+'color')
plt.imshow(own_image)
plt.axis('off')
plt.show()
```

gaussian smoothing gray image - color

own kernel (sharpening) gray image - color