## Convolution

The convolution of two functions $f$ and $g$ is defined as:

$$
(f * g)(x, y)=\sum_{v=-\infty}^{\infty} \sum_{u=-\infty}^{\infty} f(u, v) g(x-u, y-v)
$$

Where $f(x, y)$ is a function that represents the image and $g(x, y)$ is a function that represents the kernel.
In practice, the kernel is only defined over a finite set of points, so we can modify the definition to:

$$
(f * g)(x, y)=\sum_{v=y-h}^{y+h} \sum_{u=x-w}^{x+w} f(u, v) g(x-u, y-v)
$$

Where $2 w+1$ is the width of the kernel and $2 h+1$ is the height of the kernel.
$g$ is defined only over the points $[-w, w] \times[-h, h]$


- Consider the above 3 by 3 kernel with weights $\alpha_{i j}$.
- We can write the convolution Image I_old by the above kernel as:
$I_{-} \operatorname{new}(x, y)=\sum_{j=-1}^{1} \sum_{i=-1}^{1} \alpha_{i j} I \_$old $(x-i, y-j)$
If all $\alpha_{i j}$ are positive we can normalise the kernel.
$I_{-}$new_normalized $(x, y)=\frac{1}{\sum_{j=-1}^{1} \sum_{i=-1}^{1} \alpha_{i j}} \sum_{j=-1}^{1} \sum_{i=-1}^{1} \alpha_{i j} I_{-}$old $(x-i, y-j)$
Why normalizing is important?


## Convolution Pseudocode

Pseudocode for the convolution of an image $f(x, y)$ with a kernel $k(x, y)$ ( $2 w+1$ columns, $2 h+1$ lines) to produce a new image $g(x, y)$ :
for $y=0$ to ImageHeight do
for $\mathrm{x}=0$ to ImageWidth do
sum = 0
for $\mathrm{i}=-\mathrm{h}$ to h do

$$
\text { for } j=-w \text { to w do }
$$

sum $=\operatorname{sum}+k(j, i) * f(x-j, y-i)$
end for
end for
$g(x, y)=$ sum
end for
end for

Kernel axis


## Convolution equation for a 3 by 3 kernel

The pixel value $p(x, y)$ of image $f$ after convolution with a 3 by 3 kernel k is:

$$
\begin{aligned}
p(x, y) & =\sum_{i=-1}^{i=+1} \sum_{j=-1}^{j=+1} k(j, i) f(x-j, y-i) \\
& =k(-1,-1) f(x+1, y+1)+ \\
& =k(0,-1) f(x, y+1)+ \\
& =k(1,-1) f(x-1, y+1)+ \\
& =k(-1,0) f(x+1, y)+ \\
& =k(0,0) f(x, y)+ \\
& =k(1,0) f(x-1, y)+ \\
& =k(-1,1) f(x+1, y-1)+ \\
& =k(0,1) f(x, y-1)+ \\
& =k(1,1) f(x-1, y-1)
\end{aligned}
$$

| Kernel k |  |  |  |
| :---: | :---: | :---: | :---: |
| 1 | $k(-1,1)$ | $k(0,1)$ | $k(1,1)$ |
| 0 | $k(-1,0)$ | $k(0,0)$ | $k(1,0)$ |
| -1 | $k(-1,-1)$ | $k(0,-1)$ | $k(1,-1)$ |
|  | -1 | 0 | 1 |

## Convolution examples

Do the convolution of the following kernel $k$ with the image I :


## Convolution - Potential Problems

Summation over a neighbourhood might exceed the range and/or sign permitted in the image format:

- The data may need to be temporarily stored in a 16 - 32 bit integer representation.
- Then normalised back to the appropriate range (0-255 for an 8 bit image).

Another issue is how to deal with image borders:

- Convolution is not possible if part of the kernel lies outside the image.
- What is the size of image window which is processed normally when performing a Convolution of size $\mathrm{m} \times \mathrm{n}$ on an original image of size $\mathrm{M} \times \mathrm{N}$ ?


## Convolution Border Issues

How to deal with convolution at image borders:

1) Extend image limits with 0 s (Zero padding)
2) Extend image limits with own image values
3) Generate specific filters to take care of the borders

Find the corner and border specific kernel for:

| 1 | 1 | 1 |
| :--- | :--- | :--- |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

Image top left corner filter:
Kernel center (in red)

| 1 | 1 |
| :--- | :--- |
| 1 | 1 |


| -1 | -1 | -1 |
| :---: | :---: | :---: |
| -1 | 8 | -1 |
| -1 | -1 | -1 |

Image left most column filter:
Kernel center (in red)

| -1 | -1 |
| :---: | :---: |
| -1 | 5 |
| -1 | -1 |

