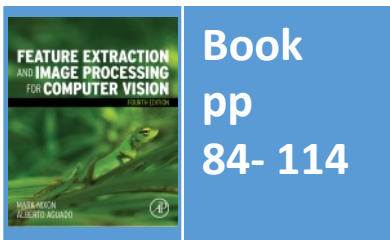


# Lecture 5 Group Operators

COMP3204 Computer Vision

**How do we combine points to make a new point in a new image?**



**Department of  
Electronics and  
Computer Science**

UNIVERSITY OF  
**Southampton**  
School of Electronics  
and Computer Science

# Content

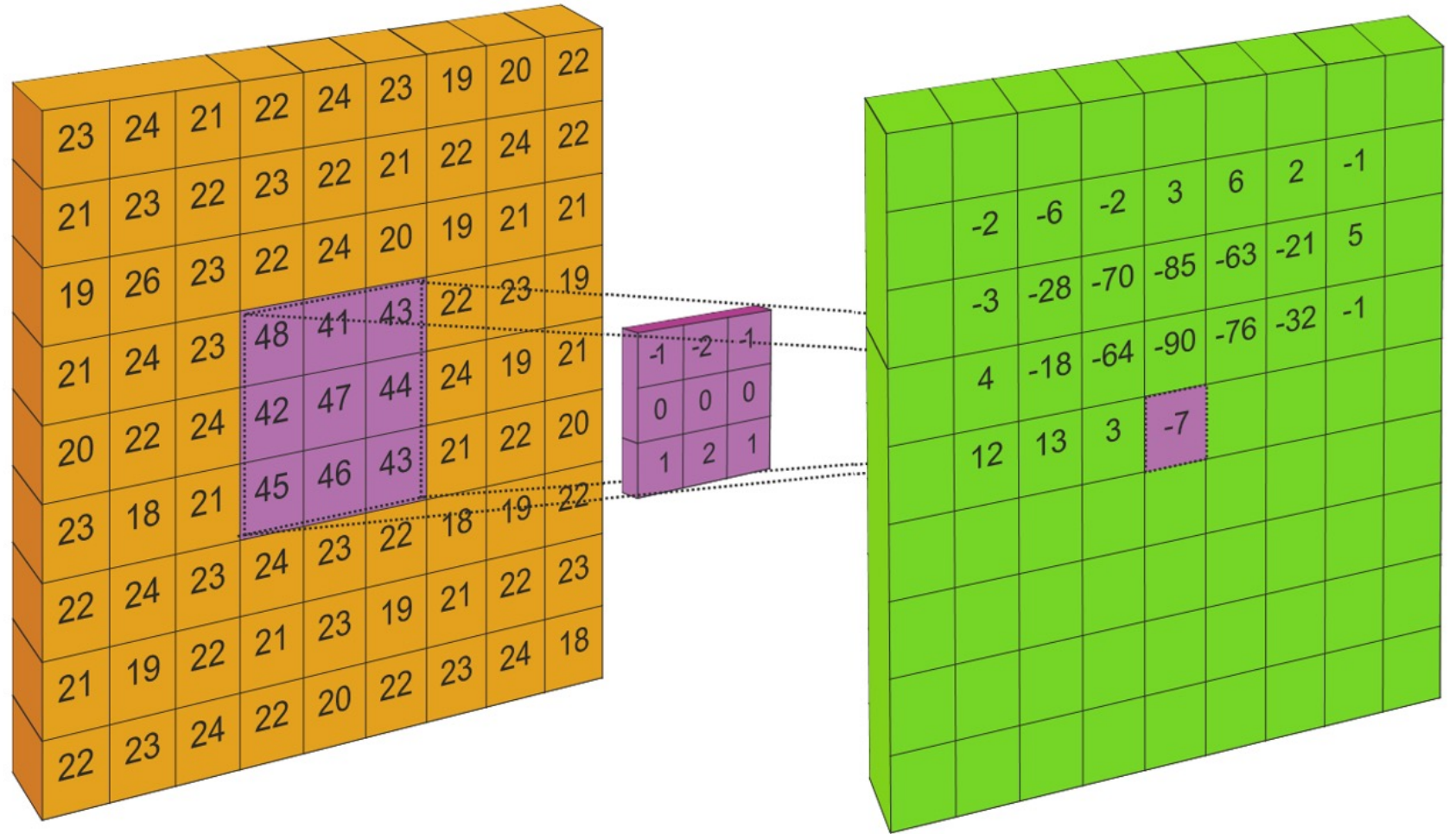
1. How can we collect points as a group?
2. How can we apply processes to that group?

# Template convolution

Calculate a **new** image from the original

**Template** is convolved in a raster fashion

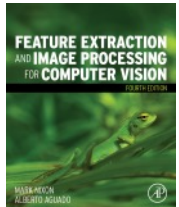
Template is **inverted** for convolution



Original image

Convolution template

Result image



# Template convolution

Image

|     |     |     |     |     |
|-----|-----|-----|-----|-----|
| 100 | 100 | 200 | 200 | 200 |
| 100 | 100 | 200 | 200 | 200 |
| 100 | 100 | 200 | 200 | 200 |
| 200 | 200 | 400 | 400 | 400 |
| 300 | 300 | 400 | 400 | 400 |

|   |     |     |   |   |
|---|-----|-----|---|---|
| 0 | 0   | 0   | 0 | 0 |
| 0 | 400 | 400 | 0 | 0 |
| 0 | 500 | 500 | 0 | 0 |
| 0 | 600 | 600 | 0 | 0 |
| 0 | 0   | 0   | 0 | 0 |

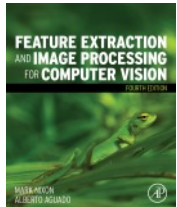
$G_y$

Result

|   |      |      |     |   |
|---|------|------|-----|---|
| 0 | 0    | 0    | 0   | 0 |
| 0 | 707  | 400  | 0   | 0 |
| 0 | 640  | 860  | 800 | 0 |
| 0 | 1000 | 1000 | 800 | 0 |
| 0 | 0    | 0    | 0   | 0 |

|   |      |      |      |   |
|---|------|------|------|---|
| 0 | 0    | 0    | 0    | 0 |
| 0 | 0    | 0    | 0    | 0 |
| 0 | -500 | -700 | -800 | 0 |
| 0 | -800 | -800 | -800 | 0 |
| 0 | 0    | 0    | 0    | 0 |

$G_x$



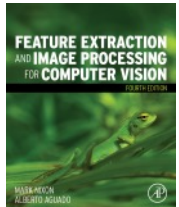
# 3×3 template and weighting coefficients

|       |       |       |
|-------|-------|-------|
| $w_0$ | $w_1$ | $w_2$ |
| $w_3$ | $w_4$ | $w_5$ |
| $w_6$ | $w_7$ | $w_8$ |

$$\mathbf{N}_{x,y} = \sum_{i \in \text{template}} \sum_{j \in \text{template}} w_{i,j} \times \mathbf{O}_{x(i),y(j)}$$

where  $w_{i,j}$  are the **weights** and  $x(i), y(j)$  denote the position of the point that matches the weighting coefficient position

Result calculated for **centre** point



# Border?

Three options

1. Set border to **black**
2. Assume **wrap-around**
3. Make **template smaller** near edges

Normally we assume object of interest is near centre so set border to **black**



# 3x3 averaging operator

$$\mathbf{N}_{x,y} = \frac{1}{9} \sum_{i \in 3} \sum_{j \in 3} \mathbf{o}_{x(i),y(j)}$$

|     |     |     |
|-----|-----|-----|
| 1/9 | 1/9 | 1/9 |
| 1/9 | 1/9 | 1/9 |
| 1/9 | 1/9 | 1/9 |



5x5,  $w = 1/25$  and 7x7,  $w = 1/49$  etc.



# Illustrating the effect of window size



3×3

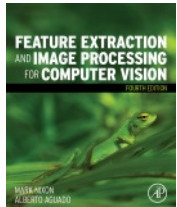


5×5



7×7

Larger operators remove more noise, but lose more detail





# Nasty bit ....

Template is actually flipped around both axes

$$\mathbf{I} * \mathbf{T} = \sum_{(x,y) \in W} \mathbf{I}_{x,y} \mathbf{T}_{i-x, j-y}$$

This does not matter for **symmetric** templates  
(i.e. the deep learning ones!)

# Template convolution via the Fourier transform

Convolution theorem allows for fast computation via FFT for template size  $\geq 7 \times 7$

$$\mathbf{P} * \mathbf{T} = \mathfrak{F}^{-1} \left( \mathfrak{F}(\mathbf{P}) \cdot \times \mathfrak{F}(\mathbf{T}) \right)$$

Template convolution \*

Fourier transform of the picture,  $\mathfrak{F}(\mathbf{P})$

Fourier transform of the template,  $\mathfrak{F}(\mathbf{T})$

Point by point multiplication ( $\cdot \times$ ) for sampled signals

This is **fast**!!

The **inversion** is **implicit** in Fourier

The theory is at end, for **information** only



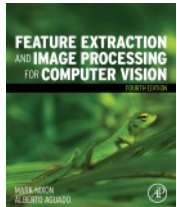
Beware of clowns ... Oxford

Imperial

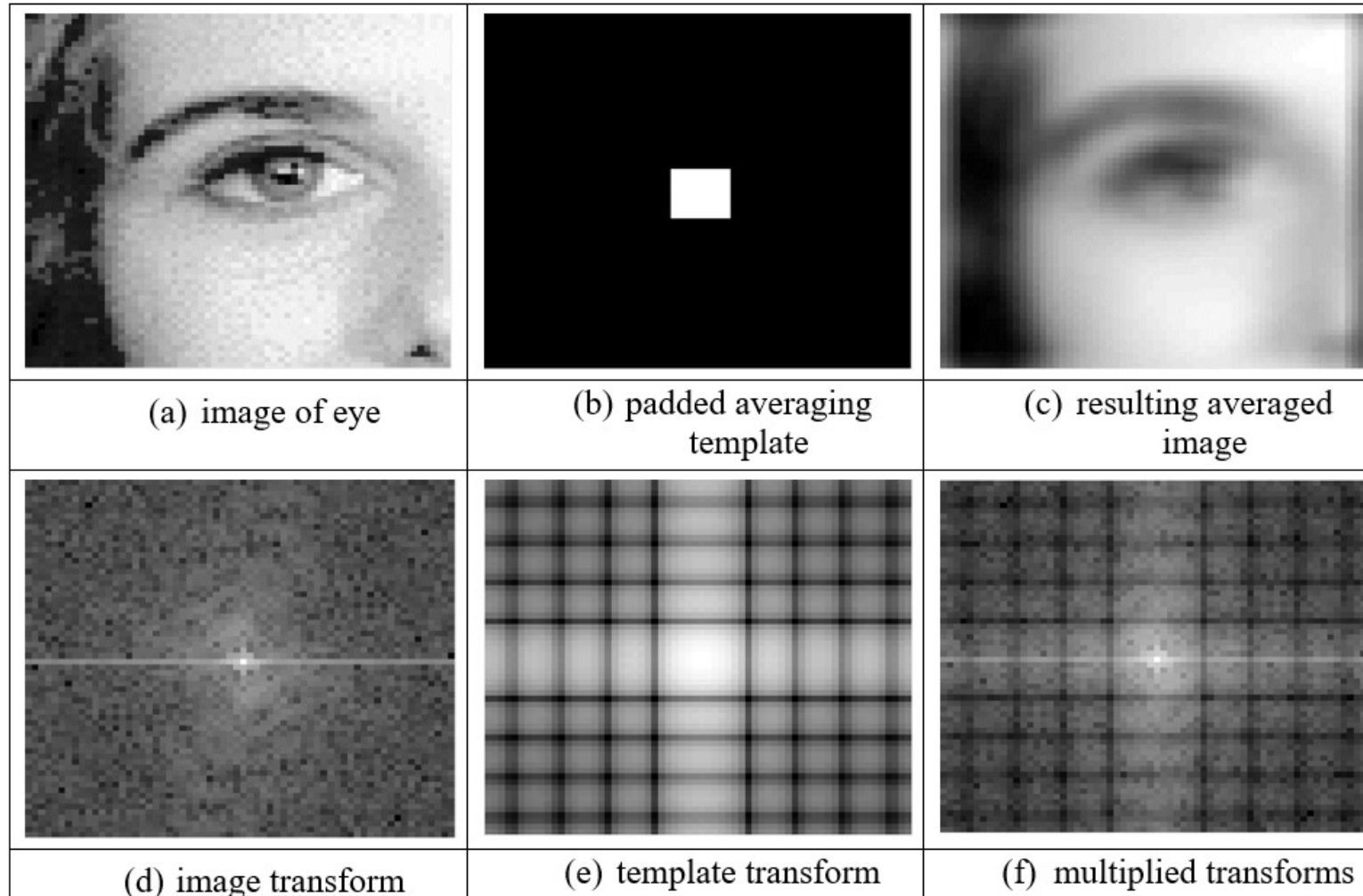
$$f(x, y) * h(x, y) \Leftrightarrow F(u, v)H(u, v)$$

$$w(t) = u(t) * v(t) \Leftrightarrow W(f) = U(f)V(f)$$

it's point by point!!



# Template Convolution via the Fourier Transform



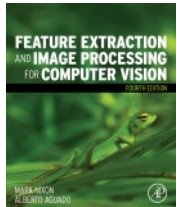
# 2D Gaussian function

$$g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

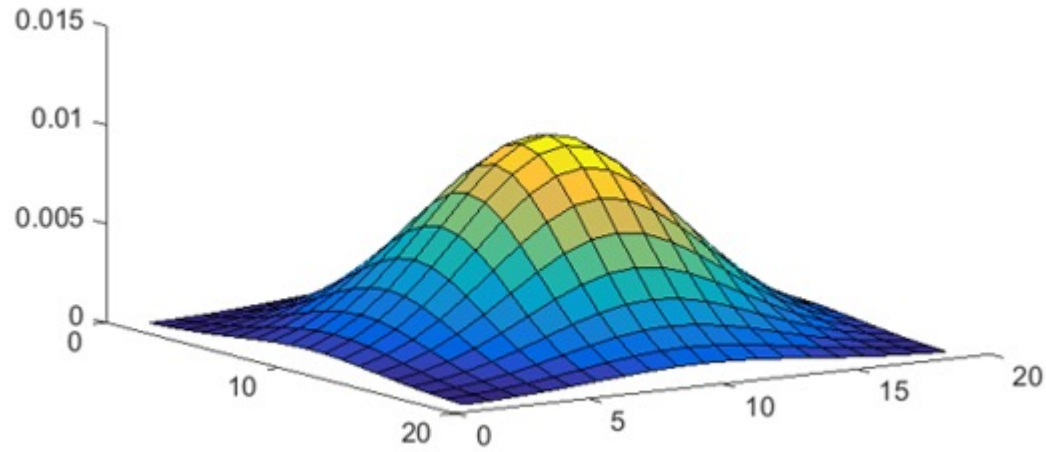
Used to calculate **template** values

Note **compromise** between **variance**  $\sigma^2$  and **window size**

Common choices 5×5, 1.0; 7×7, 1.2; 9×9, 1.4

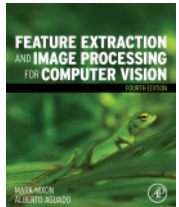


# 2D Gaussian function and template



|       |       |       |       |       |
|-------|-------|-------|-------|-------|
| 0.002 | 0.013 | 0.022 | 0.013 | 0.002 |
| 0.013 | 0.060 | 0.098 | 0.060 | 0.013 |
| 0.022 | 0.098 | 0.162 | 0.098 | 0.022 |
| 0.013 | 0.060 | 0.098 | 0.060 | 0.013 |
| 0.002 | 0.013 | 0.022 | 0.013 | 0.002 |

**Template for the  $5 \times 5$  Gaussian Averaging Operator ( $\sigma = 1.0$ )**



# Applying Gaussian averaging



**(a)**  $3 \times 3$



**(b)**  $5 \times 5$



**(c)**  $7 \times 7$

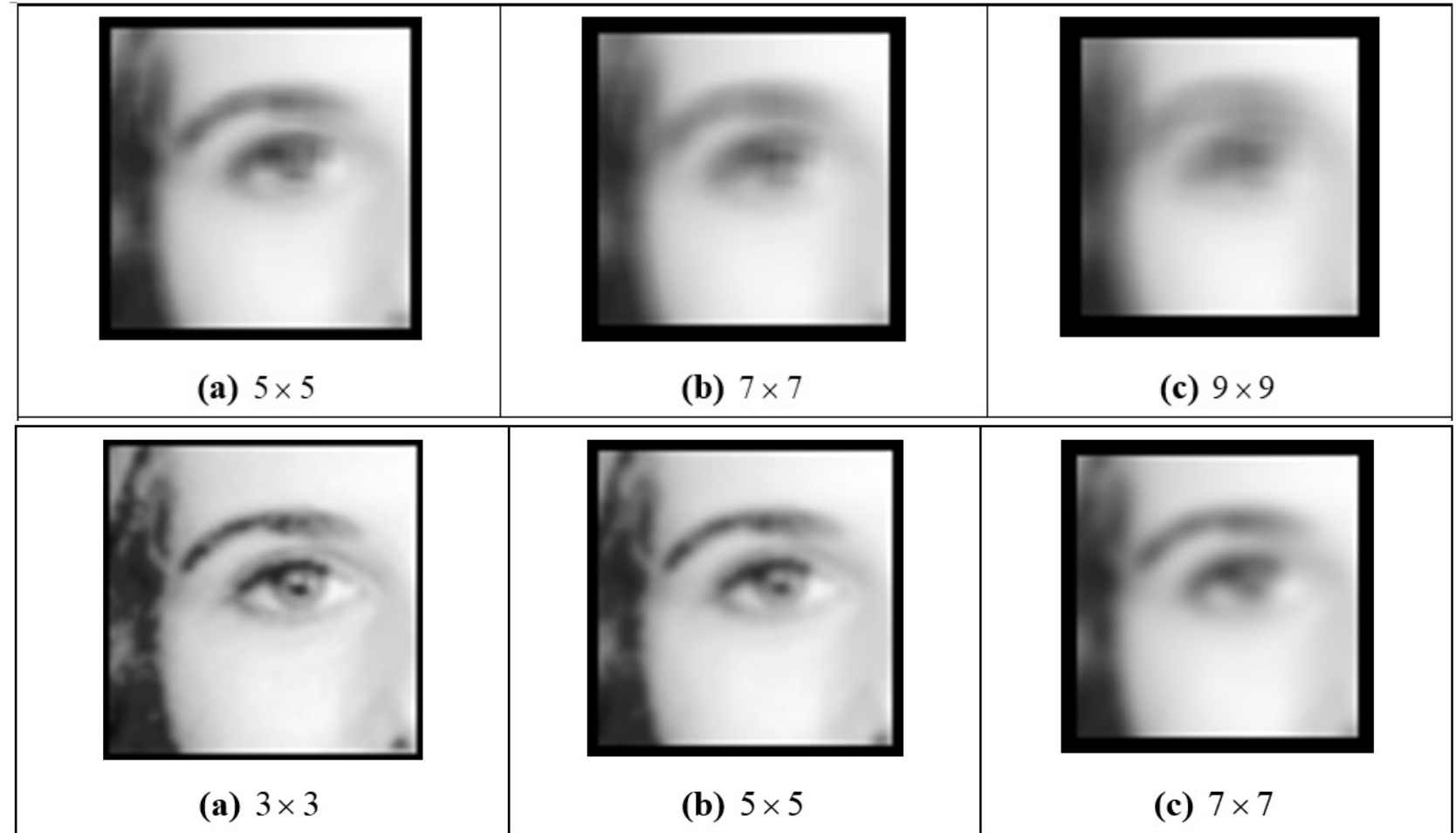


# Comparison

Direct  
averaging

Which one is  
**better?**

Gaussian  
averaging



# Finding the median from a 3×3 template

|   |   |   |
|---|---|---|
| 2 | 8 | 7 |
| 4 | 0 | 6 |
| 3 | 5 | 7 |

(a) 3×3 region

|   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|
| 2 | 4 | 3 | 8 | 0 | 5 | 7 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|

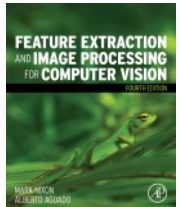
(b) unsorted vector

|   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|
| 0 | 2 | 3 | 4 | 5 | 6 | 7 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|

↑ median

(c) sorted vector, giving median

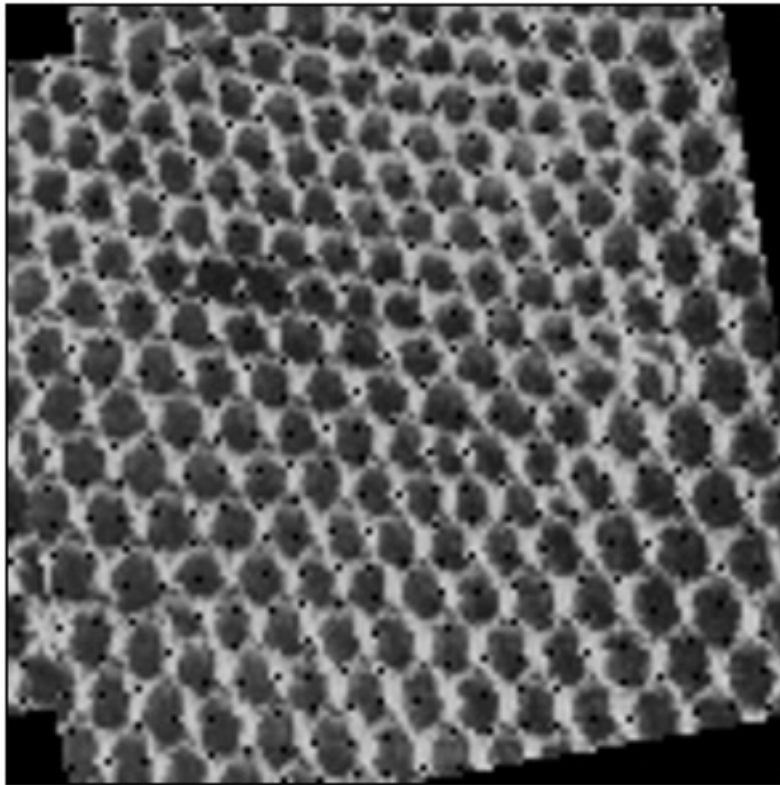
The **median** is the **centre element** of a **rank-ordered** set of template points



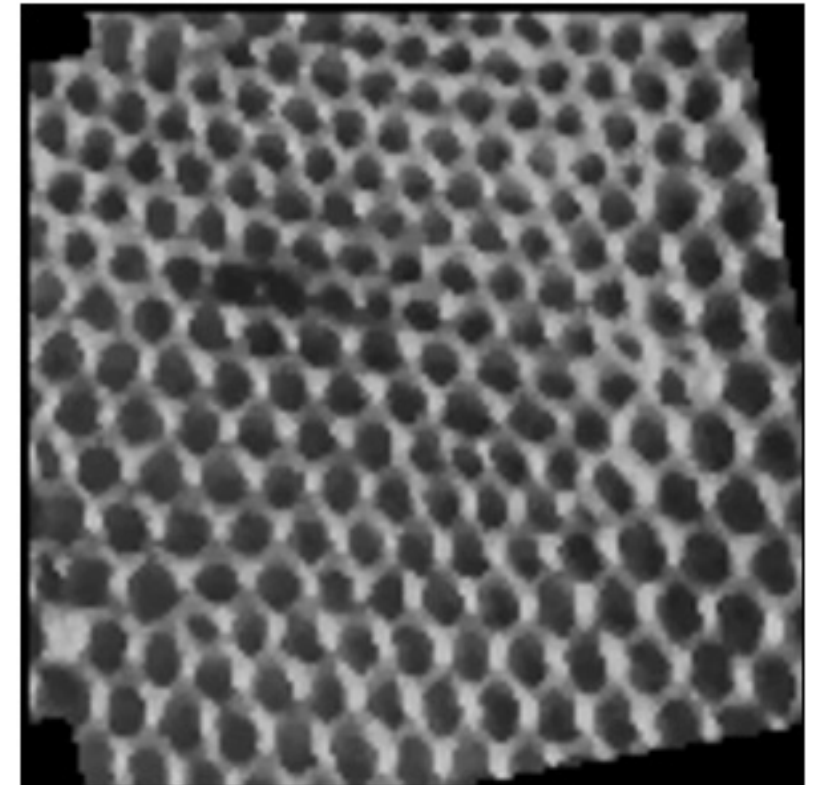


# Finding the median from a 3×3 template

Preserves **edges**; Removes **salt and pepper** noise



(a) rotated fence

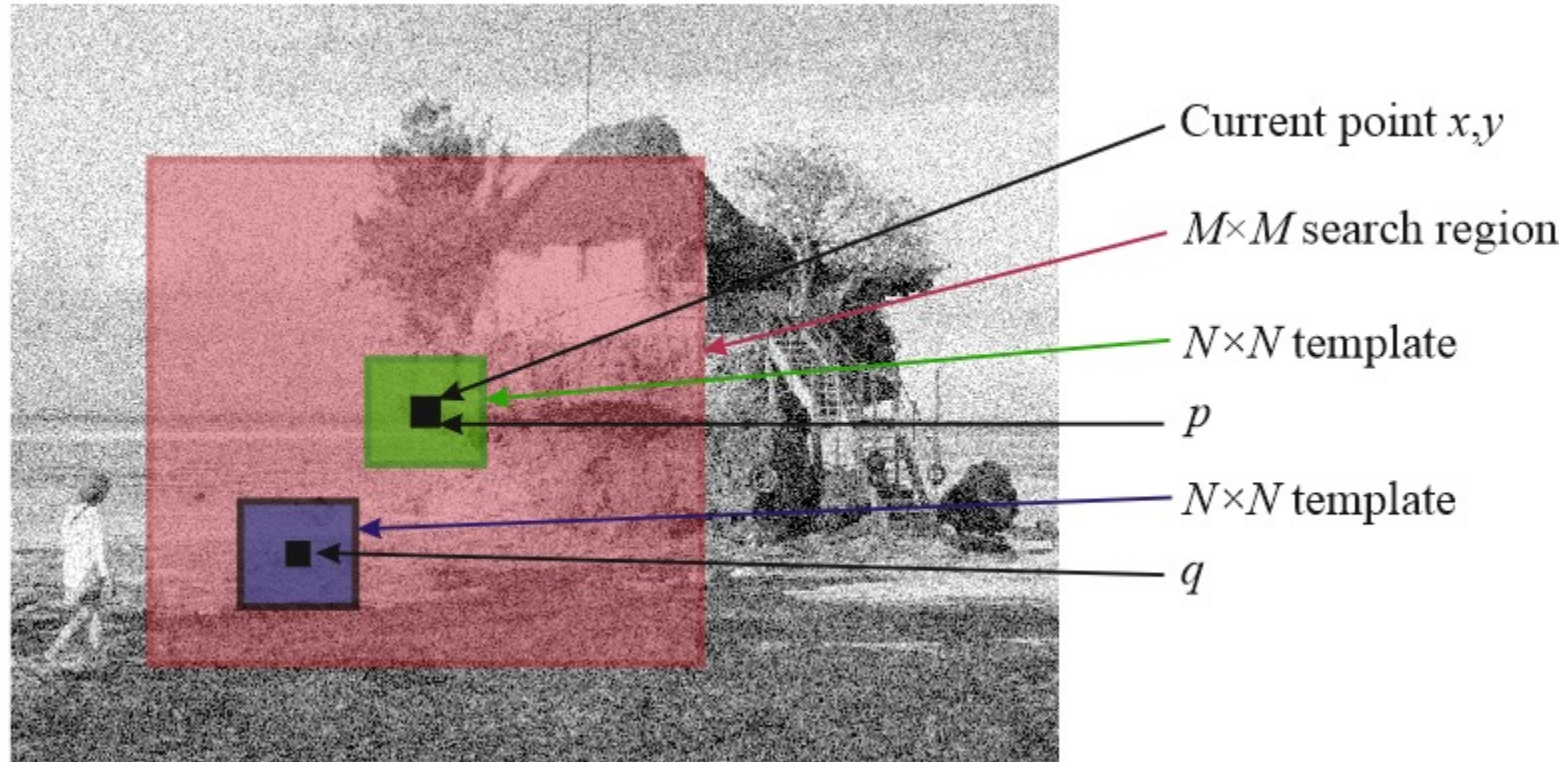


(b) median filtered



# Non-local means

Averaging which preserves regions



# Applying non local means



(a) original image



(b) Gaussian averaging



(c) nonlocal means



(a) Original



(b) (a) with added Gaussian noise



(c) Averaged



(d) Gaussian smoothed



(e) Median



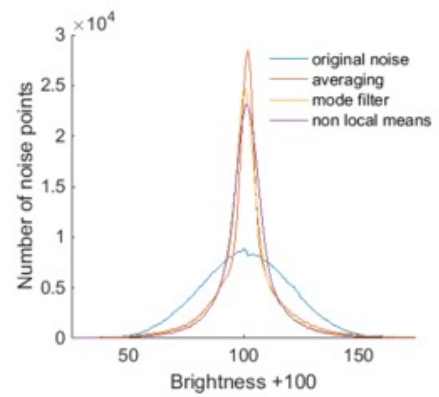
(f) Truncated Median



(g) Anisotropic diffusion



(h) Non-local-means

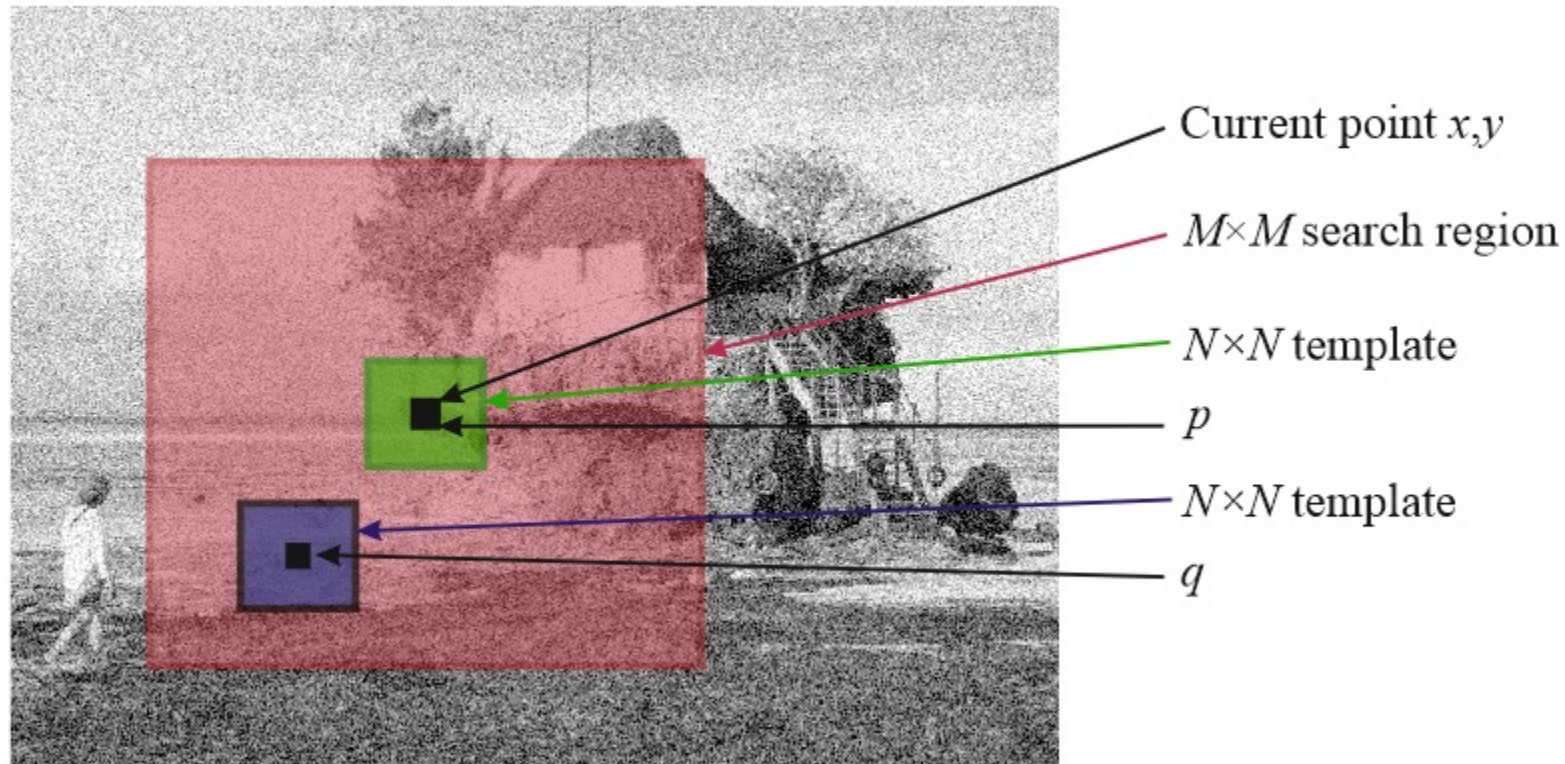


(i) Effect of filtering on noise

**Comparison of Filtering Operators**

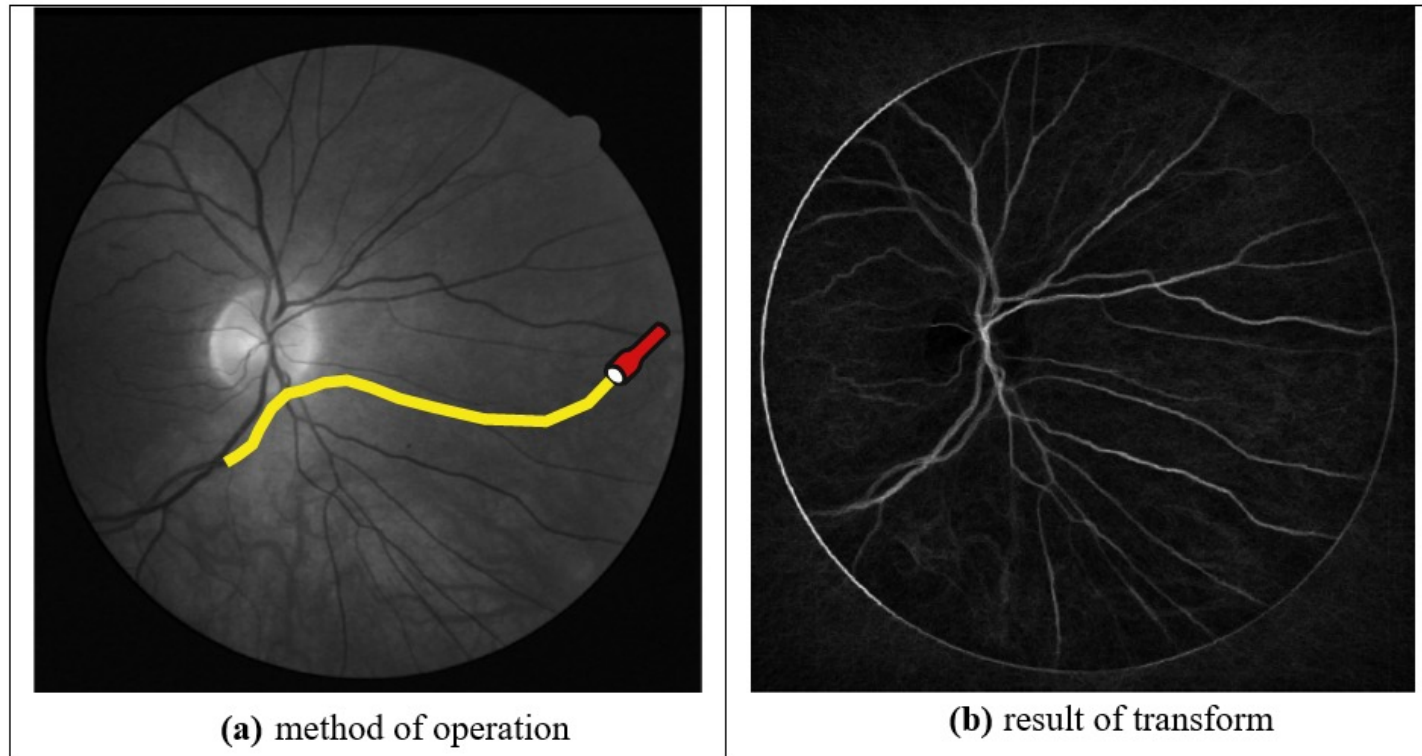
# Bilateral filtering

Averaging which preserves regions

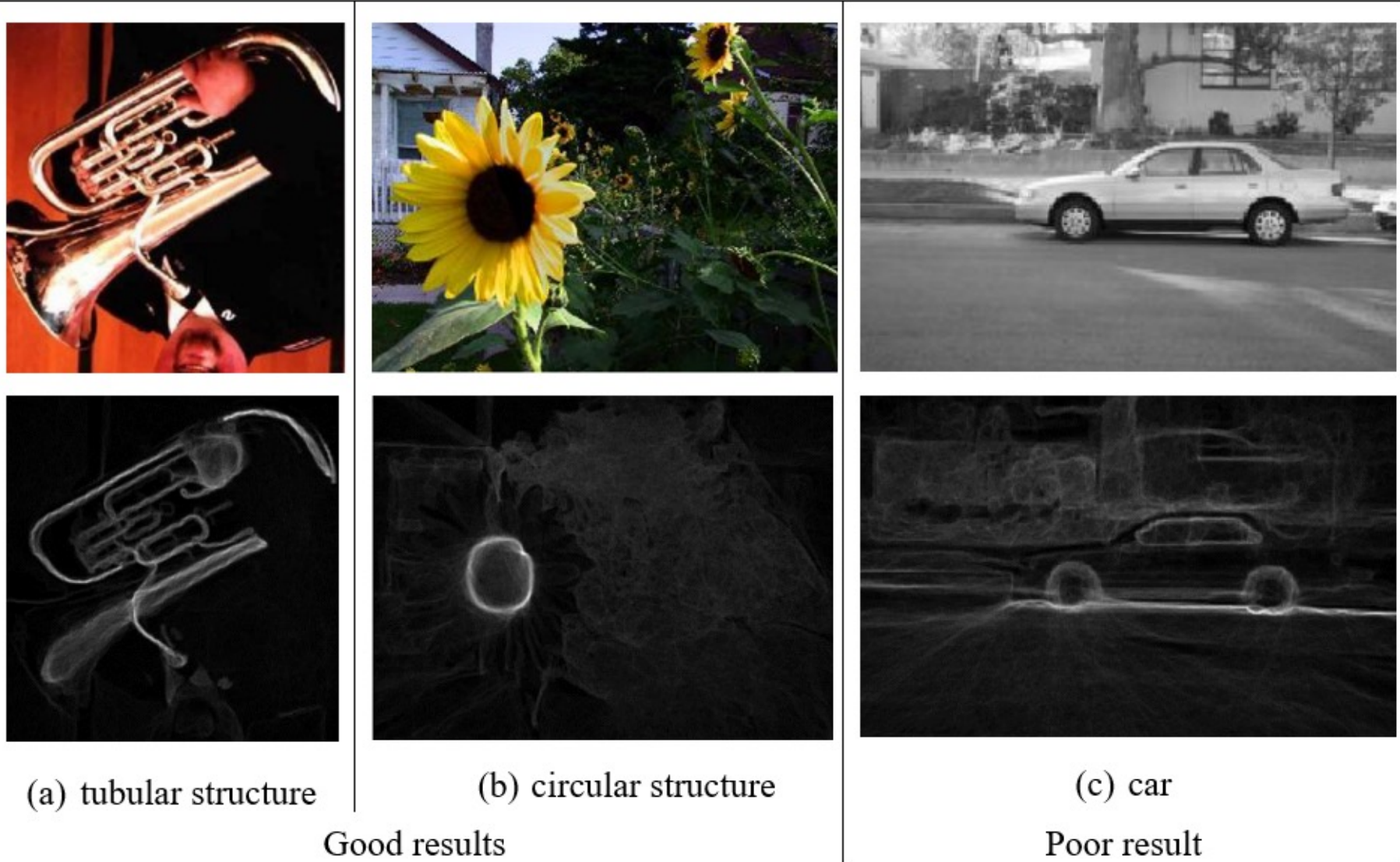


# Image Ray Transform

Use analogy to **light** to find shapes, removing remainder



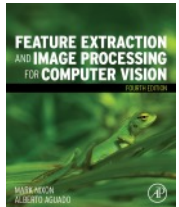
# Applying Image Ray Transform



# Main points so far

- 1 – collection of points is called a **template**
- 2 – application to an image is called **template convolution**
- 3 – can use **Fourier** to improve speed
- 4 – **averaging** reduces noise

How do we find features? That's edge detection, coming next





# Convolution theorem, for completeness only!

1-D convolution is defined as  $\mathbf{p} * \mathbf{q} = \sum_{i=0}^{N-1} p_i q_{m-i}$

by the DFT, for component  $u$   $\mathcal{F}(\mathbf{p} * \mathbf{q})_u = \frac{1}{N} \sum_{m=0}^{N-1} \left( \sum_{i=0}^{N-1} p_i q_{m-i} \right) e^{-j\frac{2\pi}{N}mu}$

by re-ordering  $= \frac{1}{N} \sum_{i=0}^{N-1} p_i \sum_{m=0}^{N-1} q_{m-i} e^{-j\frac{2\pi}{N}mu}$

by shift th<sup>m</sup>  $\mathcal{F}(\mathbf{q}[i - \Delta]) = \mathbf{Fq}[i] \times e^{-j\omega\Delta}$   $= \frac{1}{N} \sum_{i=0}^{N-1} p_i \sum_{m=0}^{N-1} q_m e^{-j\frac{2\pi}{N}mu} e^{-j\frac{2\pi}{N}iu}$

by grouping like terms  $= \frac{1}{N} \sum_{i=0}^{N-1} p_i e^{-j\frac{2\pi}{N}iu} \sum_{m=0}^{N-1} q_i e^{-j\frac{2\pi}{N}mu}$

and (by serendipity?)  $= \left( \mathcal{F}(\mathbf{p}) \times \mathcal{F}(\mathbf{q}) \right)_u$

By this, the implementation of discrete convolution using the DFT is achieved by multiplication. For two sampled signals each with  $N$  points we have

$$\mathcal{F}(\mathbf{p} * \mathbf{q}) = \mathcal{F}(\mathbf{p}) \times \mathcal{F}(\mathbf{q})$$

So convolution is the point-wise multiplication of the two transforms, and the template does not need to be inverted. The inversion is implicit in the use of the Fourier transform.

$$F_{f * g}(\omega) = F_f(\omega) \times F_g(\omega)$$

F: Fourier transform

Proof: 
$$F_{f * g}(\omega) = \int_{-\infty}^{+\infty} f * g(t) e^{j\omega t} dt$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(\tau) g(t-\tau) d\tau e^{j\omega t} dt$$

$$= \int_{-\infty}^{+\infty} \left( \int_{-\infty}^{+\infty} g(t-\tau) e^{j\omega(t-\tau)} dt \right) f(\tau) e^{j\omega\tau} d\tau$$

$$= \int_{-\infty}^{+\infty} F_g(\omega) \cdot f(\tau) \cdot e^{j\omega\tau} d\tau$$

$$= F_f(\omega) \times F_g(\omega)$$

