

Course

« *Computer Vision* »

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Correlation and convolution

Linear spatial filtering can be described in terms of correlation and convolution.

- **Correlation:**

The process of moving a filter mask over a signal (the image in our case) and computing the sum of products at each location.

- **Convolution:**

Similar to correlation but the filter mask is first rotated by 180° .

Correlation

An example:

Suppose that we want to compute the correlation of the 1D signal:

$$f(x) = 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0$$

with the mask:

$$w(x) = 1\ 2\ 3\ 2\ 8$$

0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
1	2	3	2	8	2	3	2	8	2	3	2	8	2	8
				0	0	0	8	2	3	2	1	0	0	0

Correlation vs. Convolution

- Correlation is a **function of displacement** of the filter. The first value of correlation corresponds to zero displacement, the second corresponds to one unit displacement, and so on
- Correlating a filter w with a function that contains all 0s and a single 1 yields a result that is a copy of w , but rotated by 180°
- Convolution works exactly the same way, but the filter is rotated by 180° before the shift operations.
- A fundamental property of convolution is that convolving a function with a unit impulse yields a copy of the mask at the location of the impulse.

2D Correlation/Convolution

In case of 2D functions, like images, the correlation/convolution works in a similar manner:

- For a filter of size MxN we first pad the image with a minimum of:
 - M-1 rows at top and M-1 rows at bottom (filled with 0s)
 - N-1 cols at left and N-1 cols at right (filled with 0s)
- We shift the filter at each vertical and horizontal shift to perform the correlation/convolution operation:

Correlation:
$$(w \otimes f)(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x + s, y + t)$$

Convolution:
$$(w * f)(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x - s, y - t)$$

2D Correlation Convolution

Padded f									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(b)									
Initial position for w									
1	2	3	0	0	0	0	0	0	0
4	5	6	0	0	0	0	0	0	0
7	8	9	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(c)									
Full correlation result									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	9	8	7	0	0	0	0
0	0	0	6	5	4	0	0	0	0
0	0	0	3	2	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(d)									
Cropped correlation result									
0	0	0	0	0	0	0	0	0	0
0	9	8	7	0	0	0	0	0	0
0	6	5	4	0	0	0	0	0	0
0	3	2	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(e)									
Rotated w									
9	8	7	0	0	0	0	0	0	0
6	5	4	0	0	0	0	0	0	0
3	2	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(f)									
Full convolution result									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	1	2	3	0	0	0	0
0	0	0	4	5	6	0	0	0	0
0	0	0	7	8	9	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(g)									
Cropped convolution result									
0	0	0	0	0	0	0	0	0	0
0	1	2	3	0	0	0	0	0	0
0	4	5	6	0	0	0	0	0	0
0	7	8	9	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
(h)									

Template Matching

Image (f)



Template (w)



- How do we locate the template in the image?

=> Minimize:

$$E[i, j] = \sum_{s=-a}^a \sum_{t=-b}^b [w(s, t) - f(i + s, j + t)]^2$$

Template Matching

$$E[i, j] = \sum_{s=-a}^a \sum_{t=-b}^b [w(s, t) - f(i + s, j + t)]^2$$

$$E[i, j] = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t)^2 + f(i + s, j + t)^2 - 2 w(s, t) f(i + s, j + t)$$

Minimizing $E[i, j]$ \Rightarrow Maximizing

$$\sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(i + s, j + t) = w \otimes f(i, j)$$

Filters as Templates

- Filters offer a natural mechanism for finding simple patterns.
- Filters respond most strongly to pattern elements that look like the filter.



Correlation as a Dot Product

When performing a correlation (or a convolution):

- The response is obtained by associating image elements with filter kernel elements, multiplying the associated elements and summing
 - It is the same process as a dot product.
 - The dot product achieves its largest value when the vector representing the image is parallel to the vector representing the kernel.
- ⇒ A filter responds most strongly when it encounters an image pattern that looks like the filter.
- ⇒ But this dot product is a poor way to find patterns because the response might be large just because the image region is bright.

Correlation for Pattern Matching



$$R_{wf}[i, j] = w \otimes f(i, j) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(i + s, j + t)$$

$$R_{wf}(C) > R_{wf}(B) > R_{wf}(A)$$

However, we need $R_{wf}(A)$ to be the maximum.

Normalized Correlation for Pattern Matching

Solution: *Normalizing the correlation*

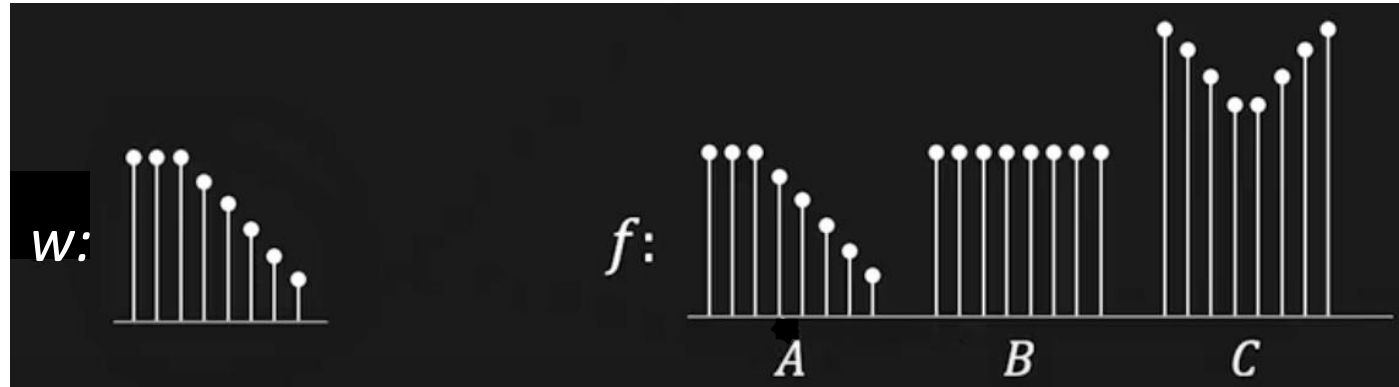
$$N_{wf}[i, j] = \frac{\sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(i + s, j + t)}{\sqrt{\sum_s \sum_t w(s, t)^2} \cdot \sqrt{\sum_s \sum_t f(i + s, j + t)^2}}$$

Energy of the template

*Energy of the image area covered
by the template*

⇒ This make the correlation insensitive to brightness.

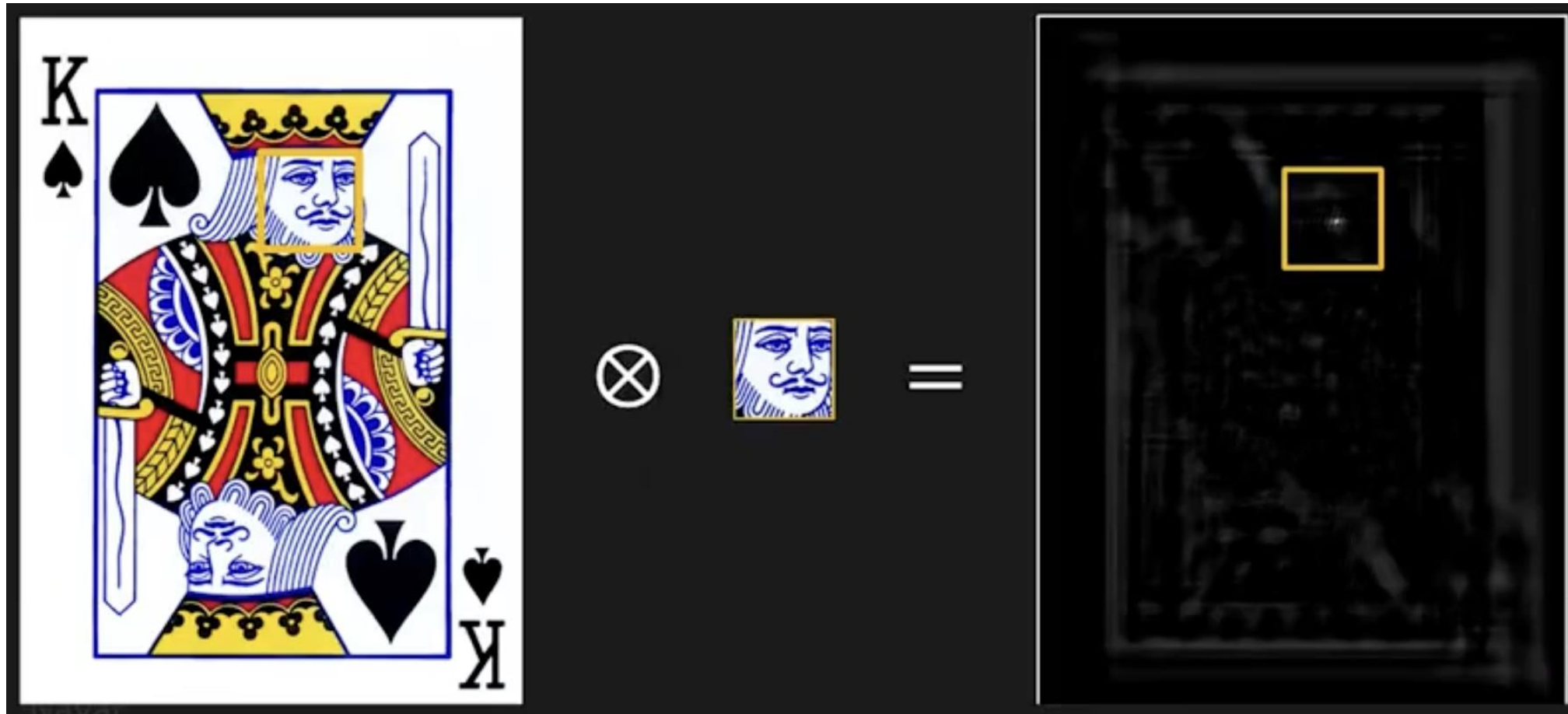
Normalized Correlation for Pattern Matching



$$N_{wf}[i, j] = \frac{\sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(i + s, j + t)}{\sqrt{\sum_s \sum_t w(s, t)^2} \cdot \sqrt{\sum_s \sum_t f(i + s, j + t)^2}}$$

$$N_{wf}A > N_{wf}(B) > N_{wf}(C)$$

Normalized Correlation for Pattern Matching



Normalized Correlation for Pattern Matching

