Video Analytics: Template Matching (Week 7)

Template Matching: Weighted Histogram

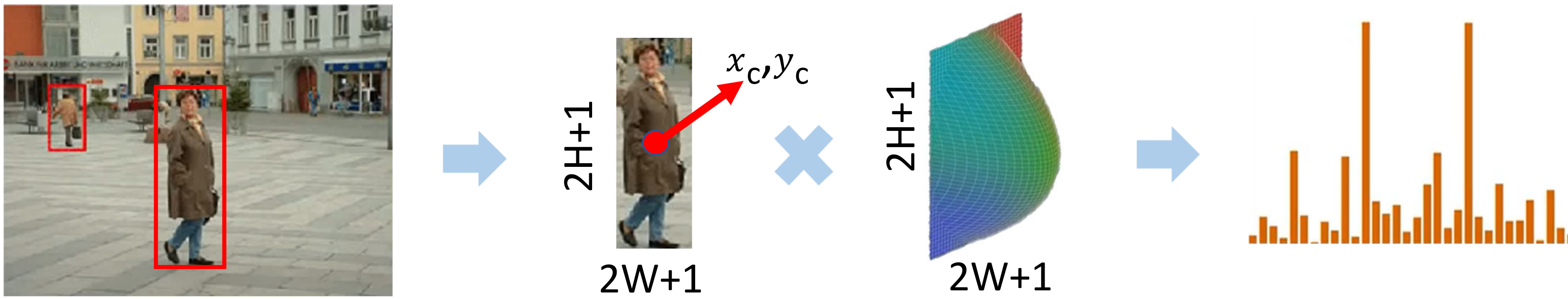


Image with object region *S*

Epanechnikov kernel

Epanechnikov kernel: $$k(\tilde{x}) = \begin{cases} 1 - \|\tilde{x}\|^2, & \|\tilde{x}\| \leq 1 \\ 0, & otherwise \end{cases}$$

where, coordinates $\tilde{x} = \begin{bmatrix} (x - x_c)/W \\ (y - y_c)/H \end{bmatrix}$

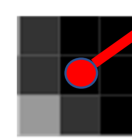
Weighted histogram gives more importance to pixels at center.

Template Matching: Weighted Histogram: DIY

- Assume a 6x6 matrix, and 3x3 template.

0	0	1	4	4	5
0	1	3	4	3	4
1	3	4	2	1	3
4	4	3	1	0	0
5	4	2	1	0	0
5	5	4	3	1	0

1	0	0
1	0	0
3	1	0



- Form a group, and evaluate weighted histogram, merge with template, and compare histograms of highlighted cells. Assume W=3, H=3.

Epanechnikov kernel: $$k(\tilde{x}) = \begin{cases} 1 - \|\tilde{x}\|^2, & \|\tilde{x}\| \leq 1 \\ 0, & otherwise \end{cases}$$

where, coordinates $\tilde{x} = \begin{bmatrix} (x - x_c)/W \\ (y - y_c)/H \end{bmatrix}$

Histogram of Oriented Gradients (Week 7)

Histogram of Oriented Gradients

- HOG is a technique to extract relevant information from the matrix.
- HOG tries to exclude redundant information of the matrix.
- HOGs are based on gradient angle and magnitude distributions, and in visual data they are robust due to the gradient's natural invariance to slight changes in ambient lighting and color variations.
- Consider a matrix $M^{n\times m}$ which is composed of $b^{3\times 3}$ non-overlapping blocks (sub-matrices), gradient estimation filters $h_x = [-1, 0, 1]$, and $h_y = [-1, 0, 1]^T$.
- Let g_x and g_y represent the gradient matrix, which can be convolved with i^{th} block:

$$g_{x_i} = b_i^{3\times 3} * h_x$$
$$g_{y_i} = b_i^{3\times 3} * h_y$$

Histogram of Oriented Gradients

- The magnitude of the gradient at each pixel for i^{th} sub-matrix can be calculated as:

$$G_i(j,k) = \sqrt{g_{x_i}(j,k)^2 + g_{y_i}(j,k)^2}$$

and the dominant gradient angle at each matrix element can be estimated by:

$$\theta_i(j,k) = tan^{-1}\left({g_{y_i}(j,k)} \Big/ {g_{x_i}(j,k)} \right)$$

- HOG features can then be generated entirely on the basis of the gradient magnitude G and gradient angles θ at each matrix element.

Histogram of Oriented Gradients: Robust Descriptors

- The primary insight provided by HOG feature extraction is that, while individual $G(j,k)$ and $\theta\ (j,k)$ are highly variable and subject to significant variations across nearby (j,k) locations, even for very similar images.
- The aggregate statistics of the spatial distribution of the gradient angles and magnitudes over small regions in similar images provide quite robust descriptors of those regions.
- The HOG opts n_θ angle bins between $0°$ and $180°$, and then distribute the estimated gradient angles and magnitudes over these bins, thus forming a more robust space which can be used to predict vital signs.

Histogram of Oriented Gradients: Robust Descriptors

- Let the edges of the n_θ bins correspond to $n_{\theta+1}$ edge values, $\varphi_z = 180 \cdot z/n_\theta$, $z = 0 \cdots n_\theta$, then a 3-D vote matrix of size $n_x \times n_y \times n_\theta$ can be defined as:

$$V\,(j,k,z) \;=\; G(j,k)\delta(\varphi_{z-1} < \; \theta(j,k) \;\leq \varphi_z), z = 1 \cdots n_\theta$$

where $\delta(\cdot)$ takes value 1 when the input argument is true, and 0 when the input argument is false.

- Resulting individual matrix element votes can be smoothed using bilinear interpolation and are then aggregated across subregions of the matrix referred to as cells. Aggregating across a particular cell c is accomplished by:

$$H(c,z) \;=\; \sum_{(j,k)\in c} V\,(j,k,z)$$

Histogram of Oriented Gradients: Robust Descriptors

- In many computer vision application areas, local changes in ambient lighting can have a significant effect on the magnitudes of feature responses.
- To tackle this issue, normalizing HOG descriptors is a fundamental step to achieve robust performance.
- HOG descriptors can be normalized using groups of neighboring cells, also called blocks. Let $N(c)$ represent the set of cells immediately surrounding the cell of interest; then the normalized HOG values can be calculated using:

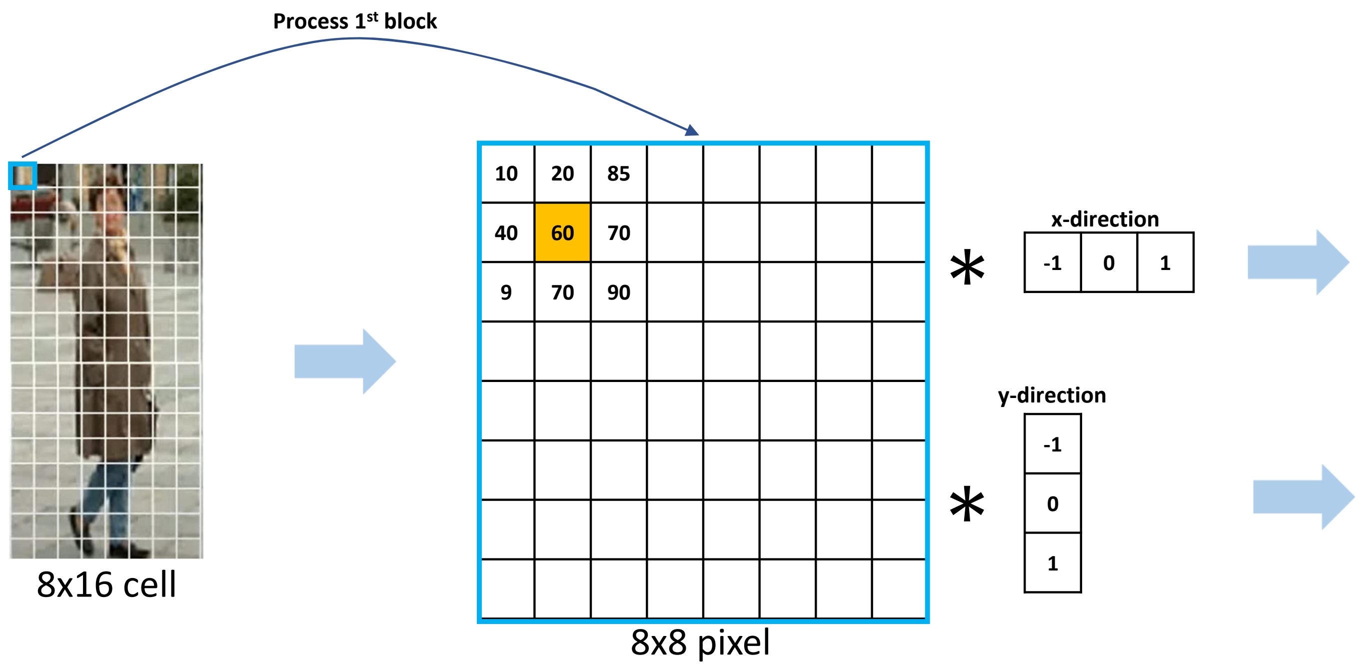
$$H'(c,z) \ = {H(c,z)} \Big/ {\sum_{c_i \in N(c)} \sqrt{\|H(ci)\|^2}}$$

where, $H(c)$ represents the vector $[H(c,1), H(c,2), \cdots, H(c,n_\theta)]^T$.

Histogram of Oriented Gradients: Application

Histogram of Oriented Gradients: Application

$$g_{x_i} = b_i^{3\times3} * h_x$$
$$g_{y_i} = b_i^{3\times3} * h_y$$
$$h_x = [-1, 0, 1]$$
$$h_y = [-1, 0, 1]^T$$



Calculate x and y directional gradients of the matrix.

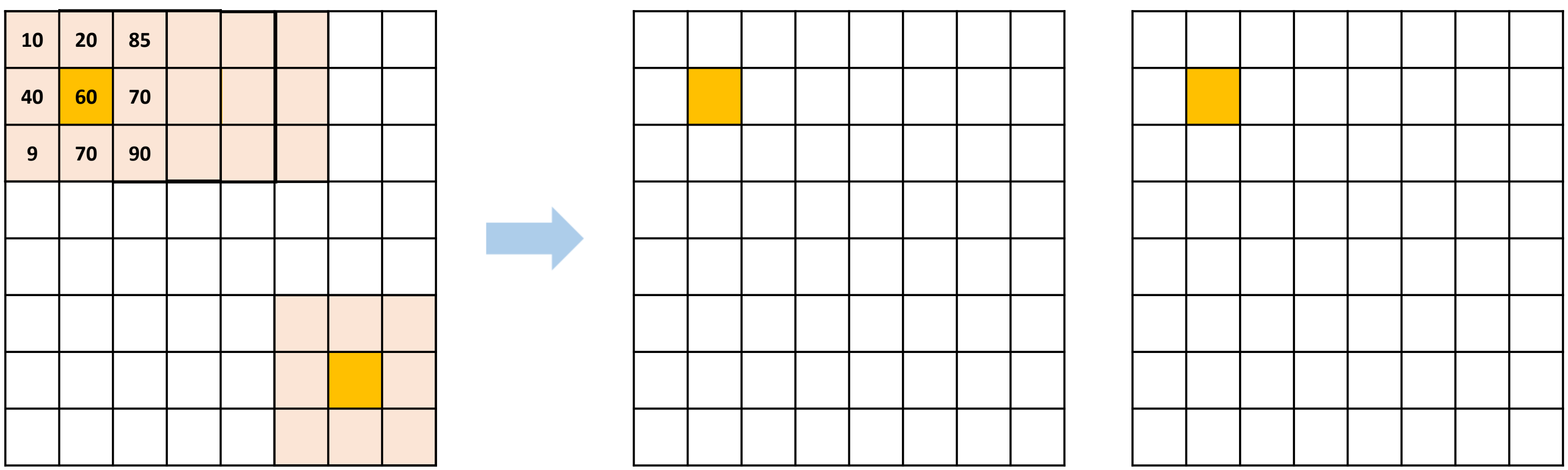
Histogram of Oriented Gradients: Application

$$G_1(2,2) = \sqrt{30^2 + 50^2} \approx 58$$

$$\theta_{1}(2,2) = tan^{-1}\left({g_{y_1}(2,2)} / {g_{x_1}(2,2)} \right) = tan^{-1}\left({50}/{30} \right) \approx 60°$$

$$G_i(j,k) = \sqrt{g_{x_i}(j,k)^2 + g_{y_i}(j,k)^2}$$

$$\theta_i(j,k) = tan^{-1}\left({g_{y_i}(j,k)} / {g_{x_i}(j,k)} \right)$$



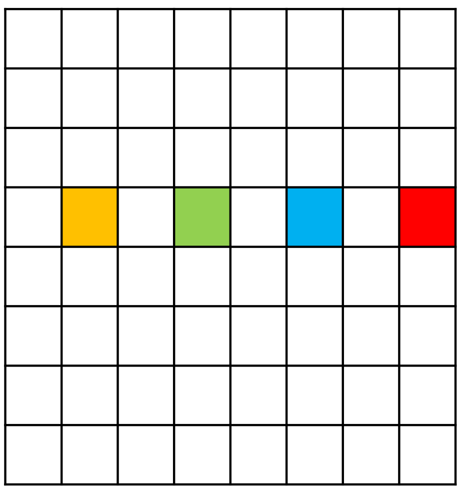
Gradient magnitude

Gradient orientation

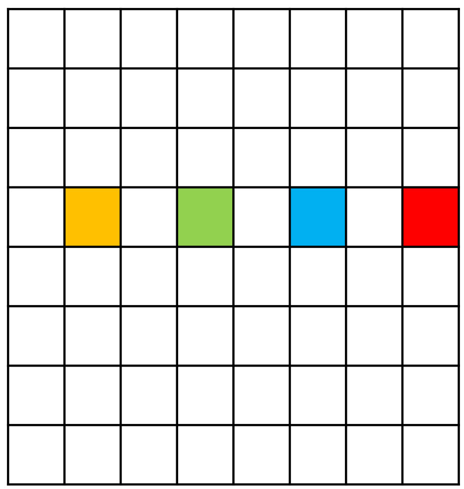
Calculate the magnitude and orientation of the matrix.

How we are going to process the remaining matrix elements situated at the edges?

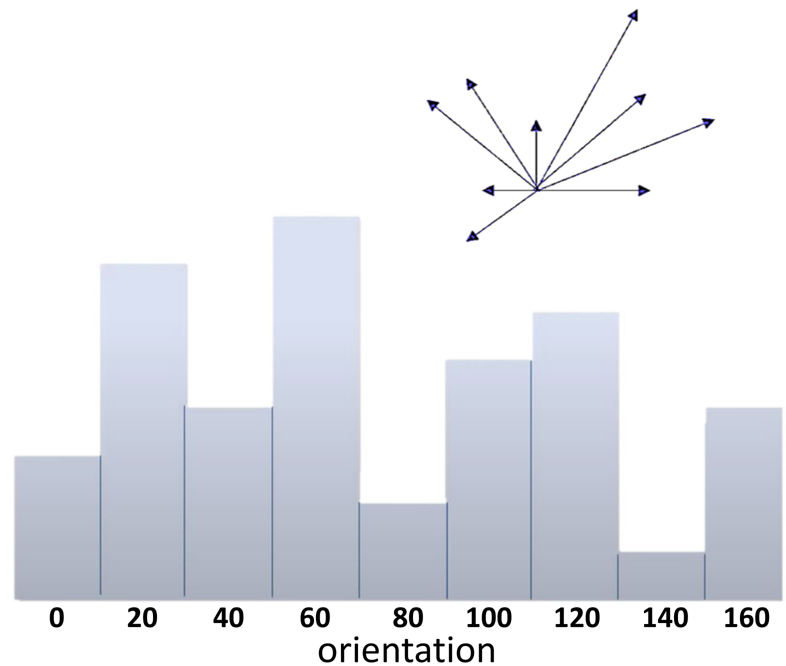
Histogram of Oriented Gradients: Application



Gradient magnitude



Gradient orientation



How we are going to assign the gradients to HOG?

Histogram of Oriented Gradients: Application

- Normalisation: It is an optional step, depending on the problem under study.

8x16

$$H'(c,z) = {H(c,z)} \Big/ {\textstyle\sum_{c_i \in N(c)} \sqrt{\|H(ci)\|^2}}$$

8x16x9 features

$\Big\Downarrow$ Transformed

7x15x36 features

What is a sense of increasing feature space in this case?

Histogram of Oriented Gradients: Application

- Normalisation: Ideally, we want our descriptor to be independent of lighting variations. In other words, we would like to "normalize" the histogram so they are not affected by lighting variations.
- Consider two cases from HOG:
  - Assume $2{,}4$ as two possible gradients. The normalising process can be performed as follows:
    $\sqrt{2^2 + 4^2} = 4.472$
    Modified gradients are: $\frac{2}{4.472}, \frac{4}{4.472} = 0.44, 0.89$
  - Assume another two gradients i.e. $4{,}8$. The normalising process can be performed as follows:
    $\sqrt{4^2 + 8^2} = 8.944$

Calculate modified gradients

Histogram of Oriented Gradients: Application