

## For Orientation Assignment

- \* SURF uses wavelet responses in horizontal and vertical direction for a neighborhood of size 6. Adequate gaussian weights are also applied to it.
- ~~\* The dominant orientation is estimated by calculating the sum of all responses can be found out using integral images very easily at any scale.~~
- \* The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of angle 60 degrees. Wavelet response could be found out using integral images very easily at any scale.
- \* For many applications, rotation invariance is not needed; hence, no need of finding the orientation, which speeds up the process.
- \* SURF provides such a functionality called Upright-SURF or U-SURF. It improves speed and is robust to upto  $\pm 15^\circ$ .

## \* For Feature Description,

→ SURF uses wavelet response in horizontal and vertical direction. A neighbourhood of size  $20 \times 20$  is taken around the keypoint where  $s$  is the size.

→ It is divided into  $4 \times 4$  subregions. For each subregions, horizontal and vertical wavelet responses are taken and a vector is formed like this,

$$v = (\sum dx, \sum dy, \sum |dx|, \sum |dy|)$$

→ This when represented as a vector ~~will~~ will give SURF feature descriptor. 64 features or dimensions. Hence, lower the dimension, higher the speed of computation and matching but provide better distinctiveness of features.

\* Another improvement over SIFT approach is that, the use of sign of Laplacian (trace of Hessian Matrix) for underlying interest point. It adds no computation cost since it is already computed during detection.



→ The sign of the Laplacian distinguishes bright blobs from dark backgrounds from the reverse situation. In the matching stage, we only compare features if they have the same type of contrast. This allows for faster matching, without reducing the descriptor's performance.

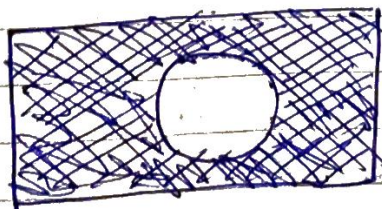
\* SURF is 3 times faster than SIFT while performance is comparable to SIFT. SURF is good at handling images with blurring and rotation, but not good at handling view-point change and illumination change.

\* Histogram of Oriented Gradiance (HOG)

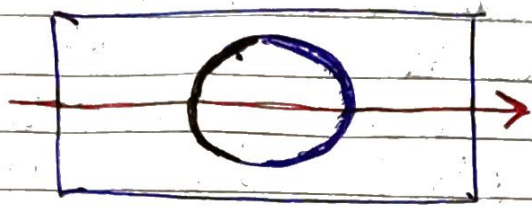
→ used for object detection

Intuition:

we have an image, with white circle in between, and the rest black.



Now we, want the horizontal gradient of the image.



The part marked in black becomes brighter.

The white color, indicates a positive gradient, i.e., change from 0 (black) to 255 (white).

The boldly marked blue part is dark in the image, this tells us the negative gradient, that is bright to dark.

So, now let's assume that in an image, there is a pixel, (the center one)

	100	
70	✓	120
	50	

So the pixels around it are 100, 70, 120, 50 (assumption)



\* Gradient in x direction:

$$120 - 70 = 50$$

\* Grad in y direction:  $100 - 50 = 50$

\* Putting it together,  $[50, 50]$  feature vector

\* After this, the magnitude and dir<sup>n</sup> are calculated as follows:

$$\text{Grad. magnitude} = \sqrt{(50)^2 + (50)^2} = 70.7$$

$$\text{Grad. Angle} = \tan^{-1}(50/50) = 45^\circ$$

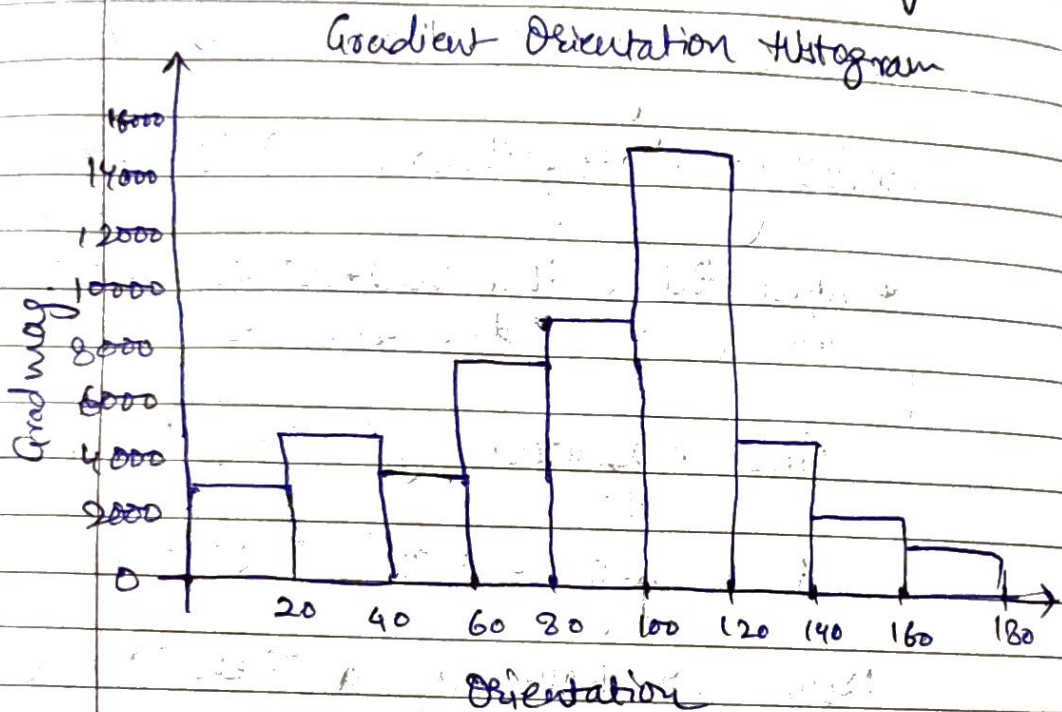
Now, we have a  $\theta$  oriented gradient from the surrounding pixels.

Oriented gradient is basically gradient of with directions.

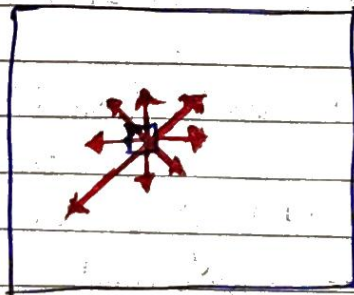
Thus, we have oriented gradients, now we want histogram of this, so we follow the following steps:

- Assuming we have an image, we use  $8 \times 8$  pixel cell, compute gradient mag/direction from SOBEL-X (grad in x dir)
- and SOBEL-Y (grad in y dir)
- Each cell is split into angular bins,

each bin corresponding to a gradient direction (9 bins,  $0-180^\circ$ ) ( $20^\circ$  each bin)  
→ This reduces 64 vectors to just 9 values



So, now we can compact the above histogram in a single vector represent<sup>n</sup>.



Hence, this makes a kind of dotted image of diff. grad with diff. mag & angles and that's how our machines see an image.



To summarize,

- HOGs are <sup>a</sup> feature descriptor used for object detection.
- HOGs along with SVM classifiers work well for obj. detection.
- HOG applies a sliding window detector over an image and HOG-descriptor is computed for each position.
- HOG takes care of the scaling issues by changing image scale (pyramiding).