

IMIP – Exercise

Vesselness Filtering & Bilateral Filtering

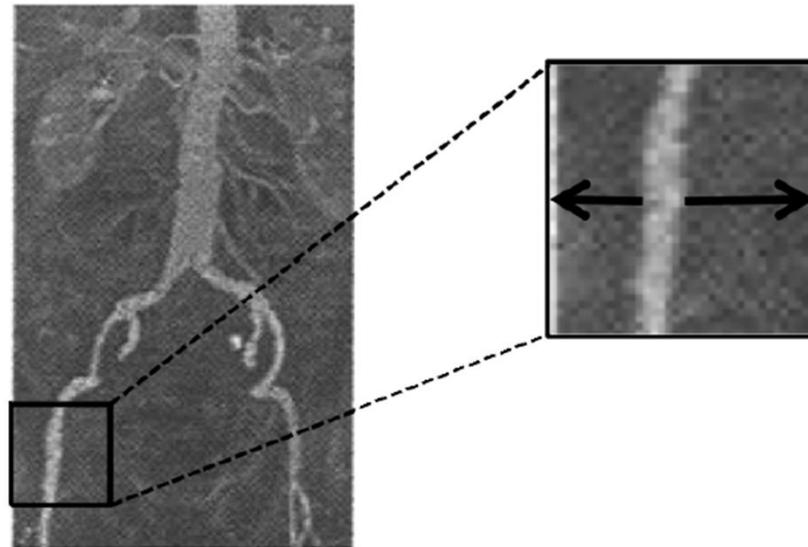
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Pattern Recognition Lab (CS 5)



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TECHNISCHE FAKULTÄT

Vessel Segmentation



- *Problem 1: Vessels appear in different diameters*
→ We need to model different scales
- *Problem 2: Edges are only a weak model of vessels*
→ Structure tensor insufficient for vessel modelling



Problem 1: Scale Modelling

- Solution using scale space s

$$I(x, s) = I(x) * G(x, s)$$
$$G(x, s) = \frac{1}{\sqrt{2\pi s^2}} e^{-\frac{\|x\|^2}{2s^2}}$$

- Derivative of Gaussians

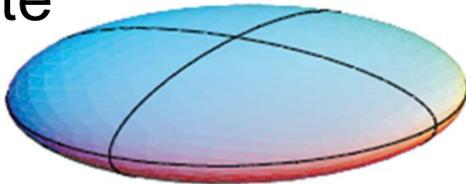
$$\frac{\delta}{\delta x} I(x, s) = I(x) * \frac{\delta}{\delta x} G(x, s)$$



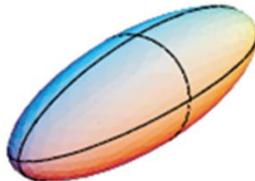
Problem 2: Vessel Model

- Edges are not a good model of a vessel
→ Compute Hessian (The second order structure is exploited for local shape properties) $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|, \lambda_n \in \mathbb{R}$

plate



line



blob

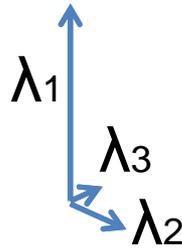
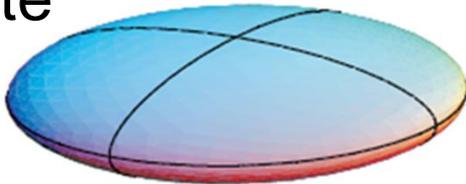




Problem 2: Vessel Model

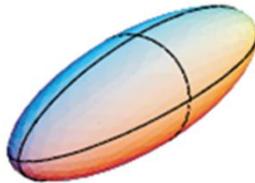
- Edges are not a good model of a vessel
→ Compute Hessian (The second order structure is exploited for local shape properties) $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|, \lambda_n \in \mathbb{R}$

plate



λ_1	λ_2	λ_3
-	0	0
+	0	0

line



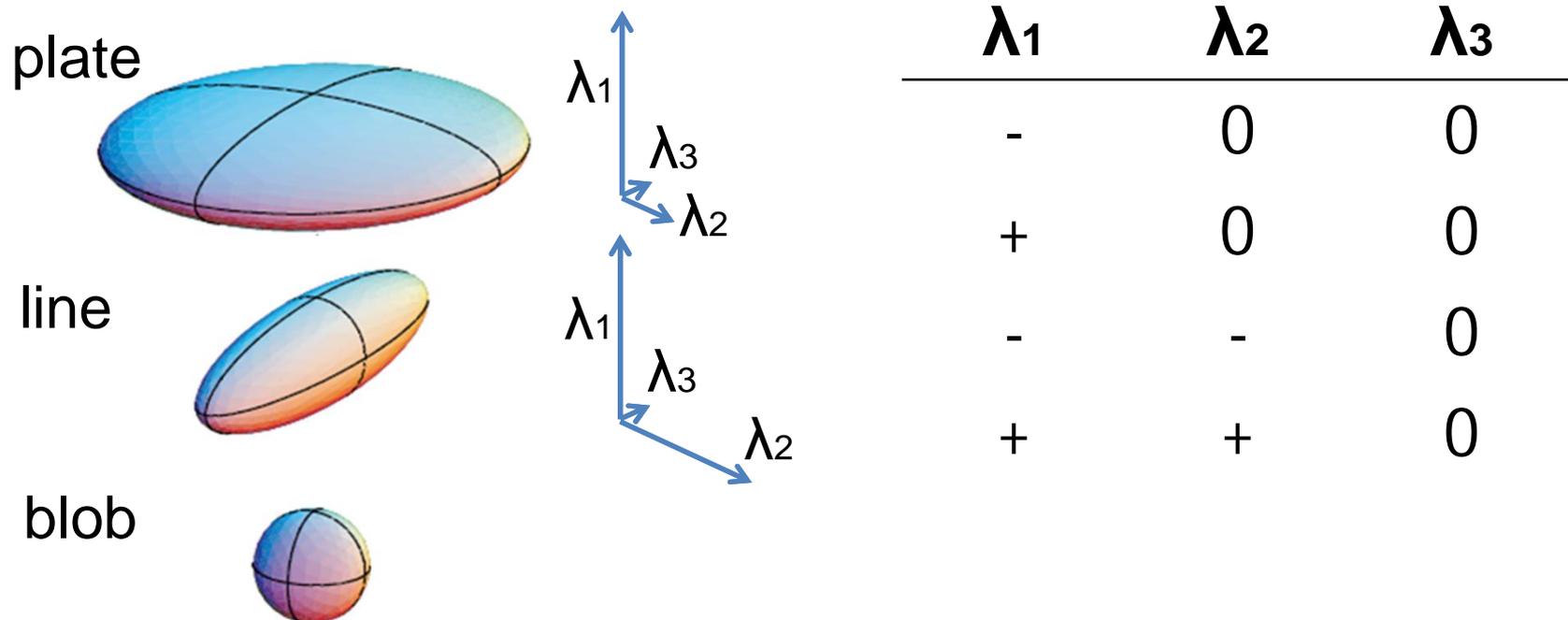
blob





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Problem 2: Vessel Model

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→ Compute Hessian (The second order structure is exploited for local shape properties) $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|, \lambda_n \in \mathbb{R}$

	λ_1	λ_2	λ_3
plate	-	0	0
line	-	-	0
blob	-	-	-

Diagram illustrating the Hessian eigenvalues ($\lambda_1, \lambda_2, \lambda_3$) for three vessel shapes: plate, line, and blob. Each shape is shown with its corresponding Hessian eigenvalue signs and magnitudes.

For the plate, λ_1 is negative, λ_2 and λ_3 are zero. For the line, λ_1 is negative, λ_2 and λ_3 are negative. For the blob, λ_1 is negative, λ_2 and λ_3 are negative.



Problem 2: Vessel Model

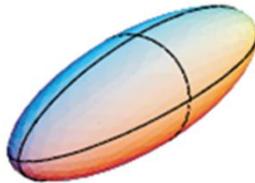
In sum, for an ideal vessel in 3D image:

$$\begin{aligned} |\lambda_3| &\approx 0 \\ |\lambda_2| &\gg \lambda_3 \\ \lambda_1 &\approx \lambda_2 \end{aligned}$$

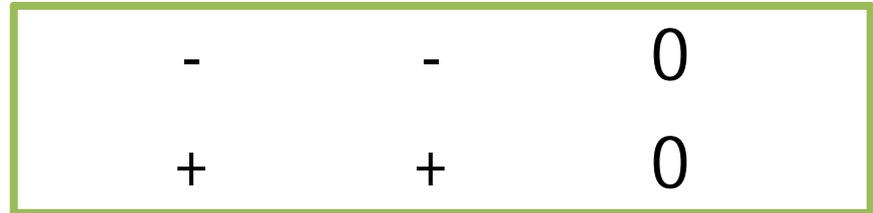
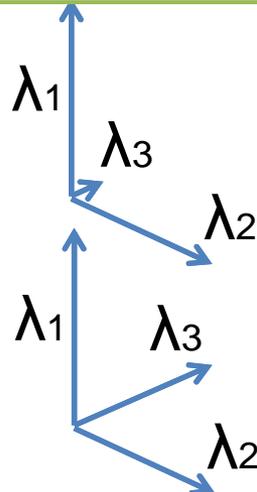
vessel
 order structure is exploited
 $\geq |\lambda_3|, \lambda_n \in \mathbb{R}$

λ_1	λ_2	λ_3
-	0	0
+	0	0
-	-	0
+	+	0
-	-	-
+	+	+

line



blob





Three vesseness measures

Deviation from blob-like structure:

$$\mathcal{R}_B = \frac{|\lambda_3|}{\sqrt{|\lambda_1 \lambda_2|}}, \quad \mathcal{R}_B \in [0, 1] \subset \mathbb{R}$$

Similarity to a plate-like structure:

$$\mathcal{R}_A = \frac{|\lambda_2|}{|\lambda_1|}, \quad \mathcal{R}_A \in [0, 1] \subset \mathbb{R}$$

Frobenius norm, second-order-like structure:

$$\mathcal{S} = \|\mathbf{H}[L(\mathbf{x})]\|_F = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}, \quad \mathcal{S} \in \mathbb{R}^{0+}$$

	λ_1	λ_2	λ_3
plate	-	0	0
	+	0	0
line	-	-	0
	+	+	0
blob	-	-	-
	+	+	+

In regions with high contrast, this norm will become larger since at least one of the eigenvalues will be large.



Problem 2: Vessel Model

- In the definition of vesselness the three properties are combined

$$V(\mathbf{x}, s) = \begin{cases} 0 \\ (1 - \exp\left(-\frac{R_A^2}{2\lambda^2}\right)) \exp\left(-\frac{R_B^2}{2\beta^2}\right) (1 - \exp\left(-\frac{S^2}{2c^2}\right)) \end{cases}$$

$\lambda, \beta, c \rightarrow$ Parameter to select by user

($\lambda = \beta = 0, 5$; c depends on contrast)

The idea behind this expression is to map the features into probability-like estimators of vesselness.



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The idea behind this expression is to map the features into probability-like estimators of vesselness.

The vesselness measure is analyzed at different scales. We integrate them to obtain the final estimate of vesselness:

$$V(\mathbf{x}) = \max_s V(\mathbf{x}, s)$$



Vessel Model in 2D (for exercise)

- Compute Hessian in 2D

$$H_s = \begin{pmatrix} \frac{\delta^2}{\delta x^2} I(x, s) & \frac{\delta^2}{\delta x \delta y} I(x, s) \\ \frac{\delta^2}{\delta y \delta x} I(x, s) & \frac{\delta^2}{\delta y^2} I(x, s) \end{pmatrix}$$

- Ideal vessel structure in 2D

$$|\lambda_1| < |\lambda_2| \quad \wedge \quad |\lambda_1| \approx 0$$

Note: in exercise we sort eigenvalues in ascending order!



Two vesselness measures

Blobness measure and second-order structure in 2D:

$$R_B = \frac{\lambda_1}{\lambda_2} \quad (\text{Close to 0, if vessel})$$

$$S = \sqrt{\lambda_1^2 + \lambda_2^2} \quad (\text{High contrast, if vessel})$$



Two vesselness measures

Blobness measure and second-order structure in 2D:

$$R_B = \frac{\lambda_1}{\lambda_2} \quad (\text{Close to 0, if vessel})$$

$$S = \sqrt{\lambda_1^2 + \lambda_2^2} \quad (\text{High contrast, if vessel})$$

Combining them into probability estimator:

$$V(\mathbf{x}, s) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \\ \exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right) & \end{cases}$$

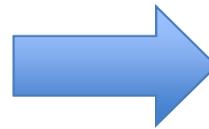
β, c : Control parameters ($\beta = 0.5$; c depends on scaling)

$$V(\mathbf{x}) = \max_{s_{\min} < s < s_{\max}} V(\mathbf{x}, s)$$



Bilateral Filtering

- *Problem:* Conventional filters smooth across edges



- *Idea:* Incorporate edge-stopping functionality based on pixel similarity





General idea

- Every sample is replaced by a weighted average of its neighbours
- These weights reflect two properties
 - How close are the neighbour and the center sample, so that that **larger weight to closer samples** (*Spatial closeness*)
 - How similar are the neighbour and the center sample – **larger weight to similar samples** (*Range similarity*)
- All the weights should be normalized to preserve the local mean



In an Equation

$$BF [I]_x = \frac{1}{W_x} \sum_{x' \in \omega_x} G_{\sigma_c} (\|x - x'\|) G_{\sigma_s} (|I(x) - I(x')|) I_{x'}$$

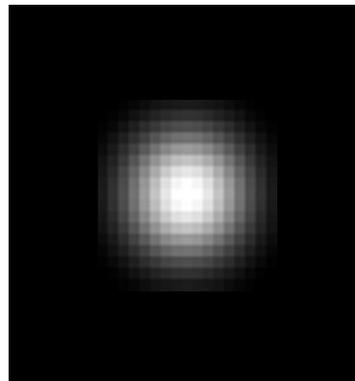


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space weight

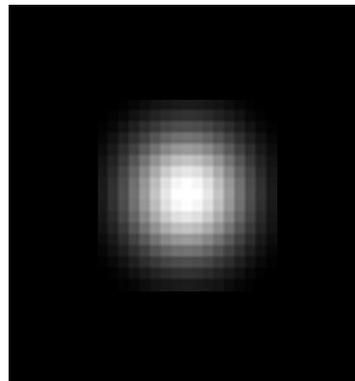




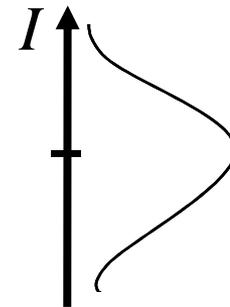
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space weight



range weight





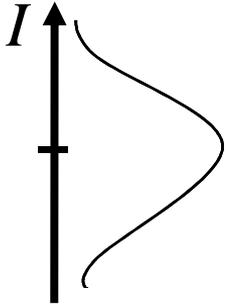
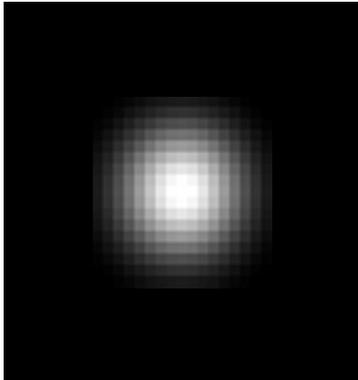
In an Equation

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normalization factor

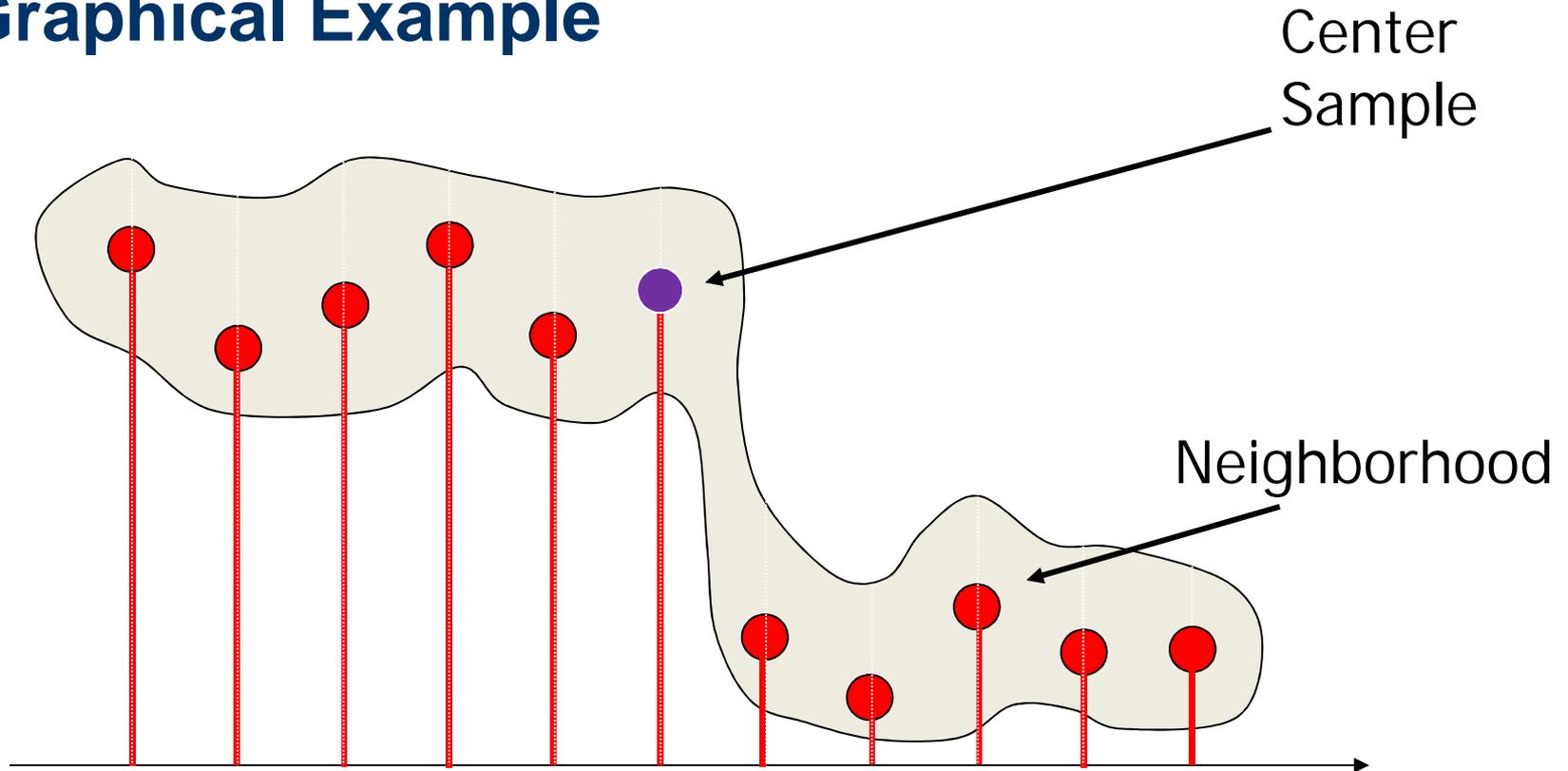
space weight

range weight





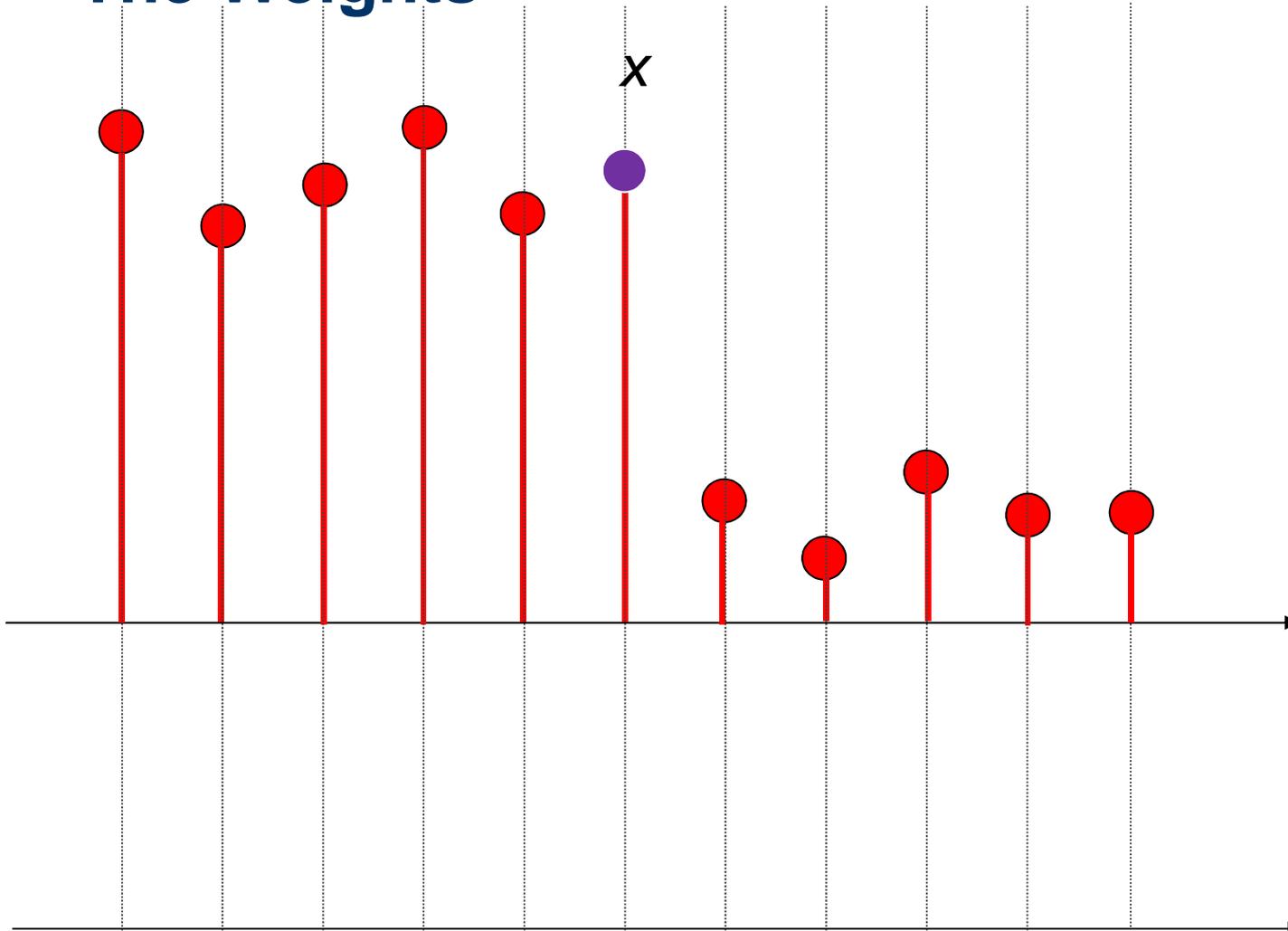
Graphical Example



It is clear that in weighting this neighborhood, we would like to preserve the step

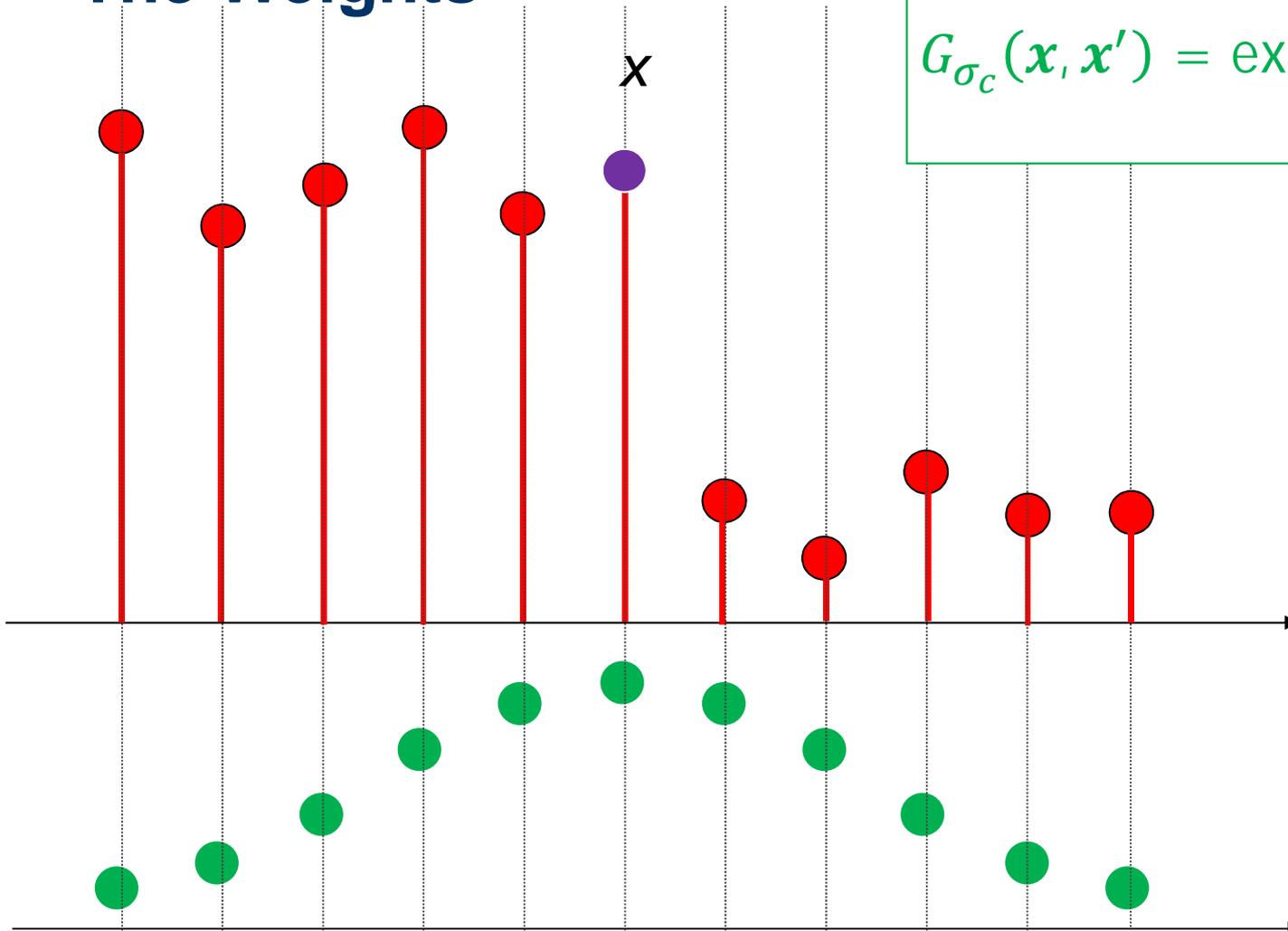


The Weights





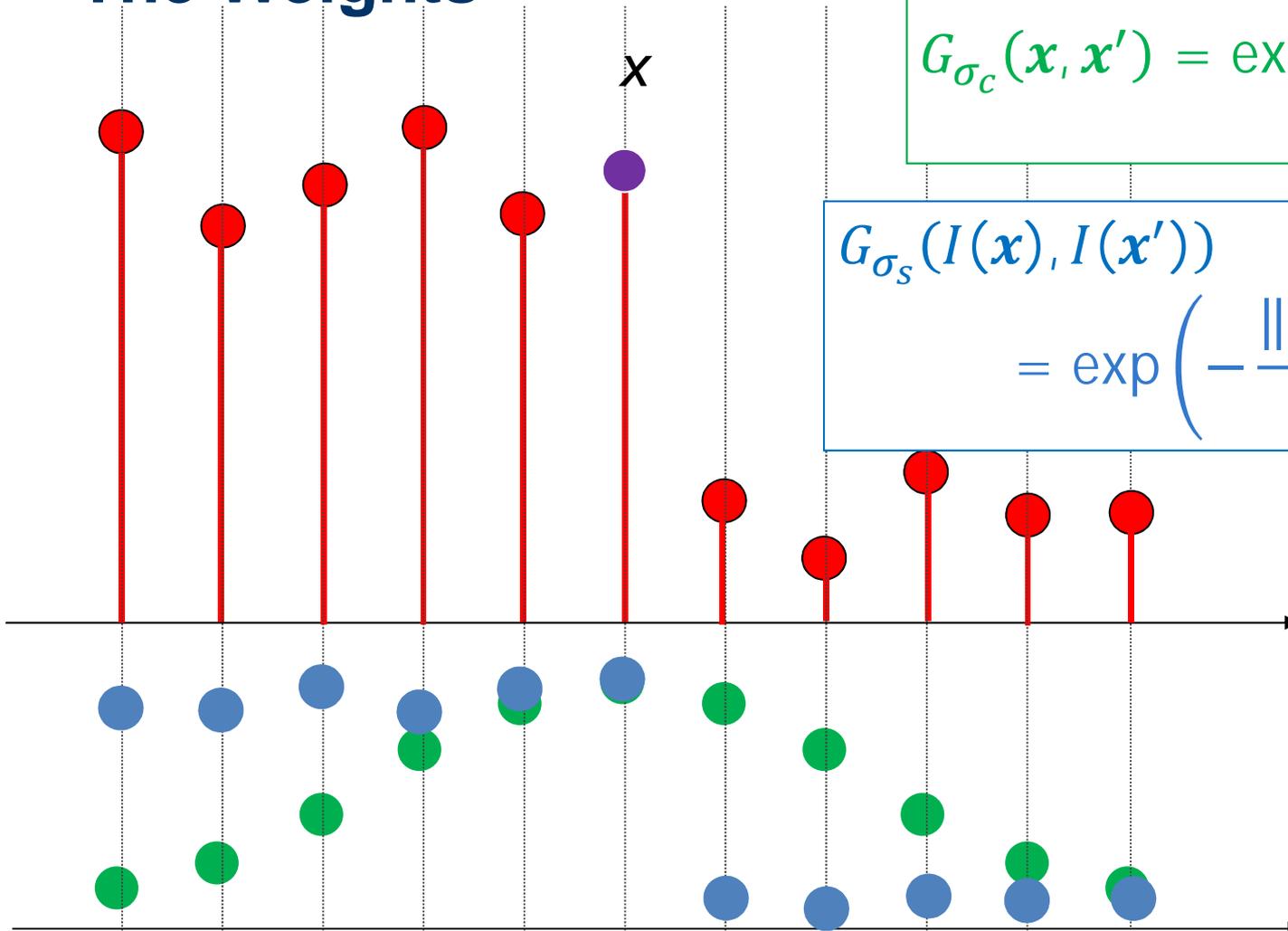
The Weights



$$G_{\sigma_c}(x, x') = \exp\left(-\frac{\|x - x'\|^2}{\sigma_c^2}\right)$$



The Weights

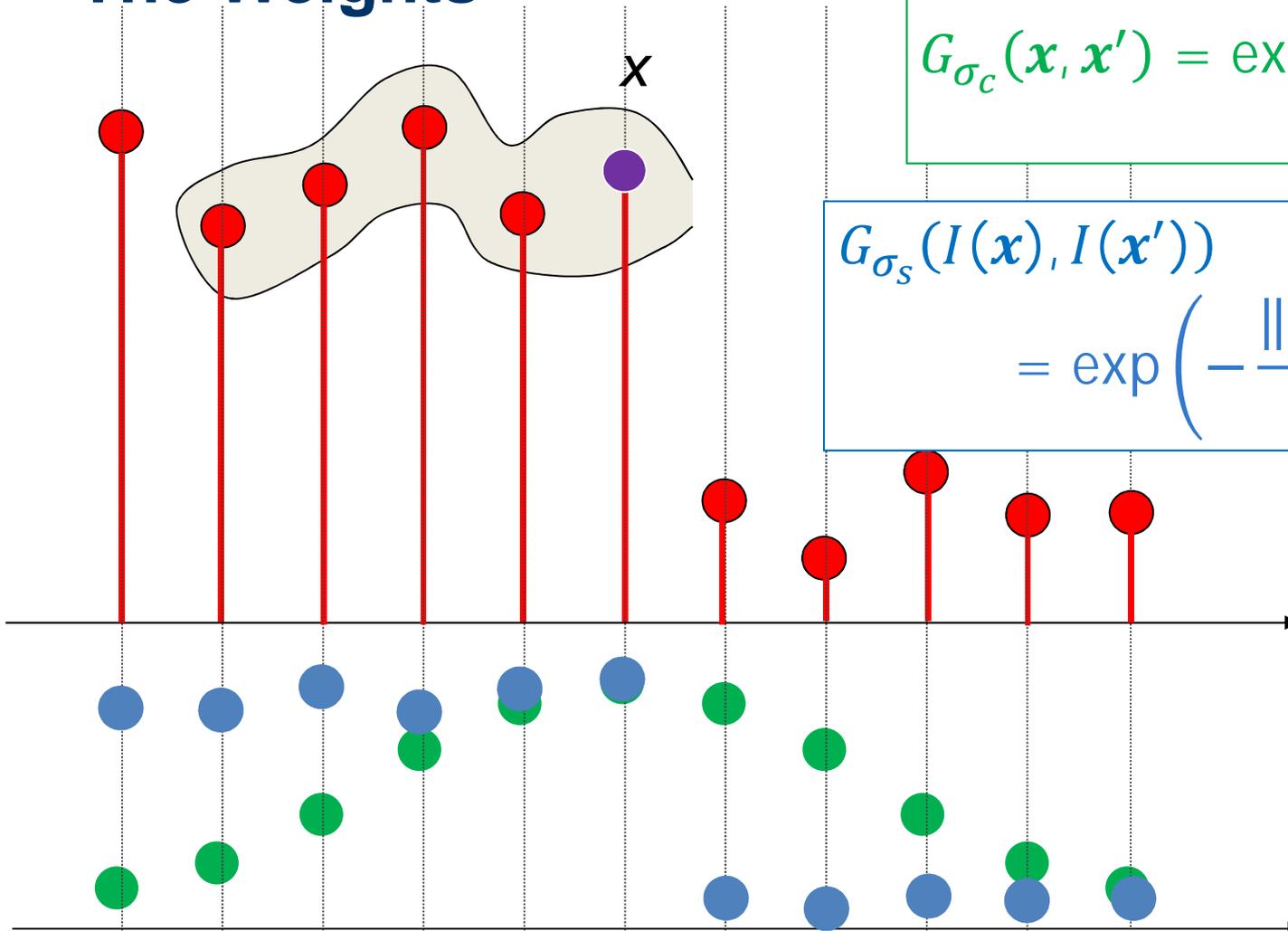


$$G_{\sigma_c}(x, x') = \exp\left(-\frac{\|x - x'\|^2}{\sigma_c^2}\right)$$

$$G_{\sigma_s}(I(x), I(x')) = \exp\left(-\frac{\|I(x) - I(x')\|^2}{\sigma_s^2}\right)$$



The Weights



$$G_{\sigma_c}(x, x') = \exp\left(-\frac{\|x - x'\|^2}{\sigma_c^2}\right)$$

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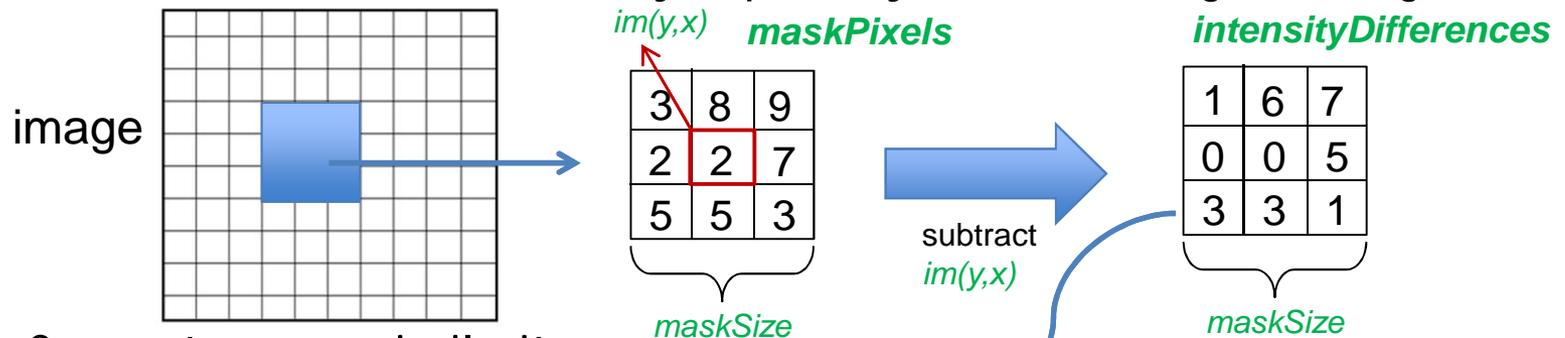
Implementation for Exercise



- Pre-computed spatial closeness in the mask (it's independent to image)

$$\text{closeness} = \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(-\frac{X^2 + Y^2}{2\sigma_c^2}\right)$$

- Compute range similarity (depends on image intensity)
 1. Extract a sub-region of the image which is inside the filter mask
 2. Get the difference of intensity in point (y,x) and its neighbouring's



3. Compute range similarity

$$\text{similarity} = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp\left(-\frac{\|I(x) - I(x')\|^2}{2\sigma_s^2}\right)$$

- Combine these two weights for each pixel inside the mask
- New intensity is obtained by a weighted average of its neighbours

$$\text{filtered}(x) = \frac{\sum_{x' \in \omega_x} I(x')W(x, x')}{\sum_{x' \in \omega_x} W(x, x')}$$