LoG vs. DoG

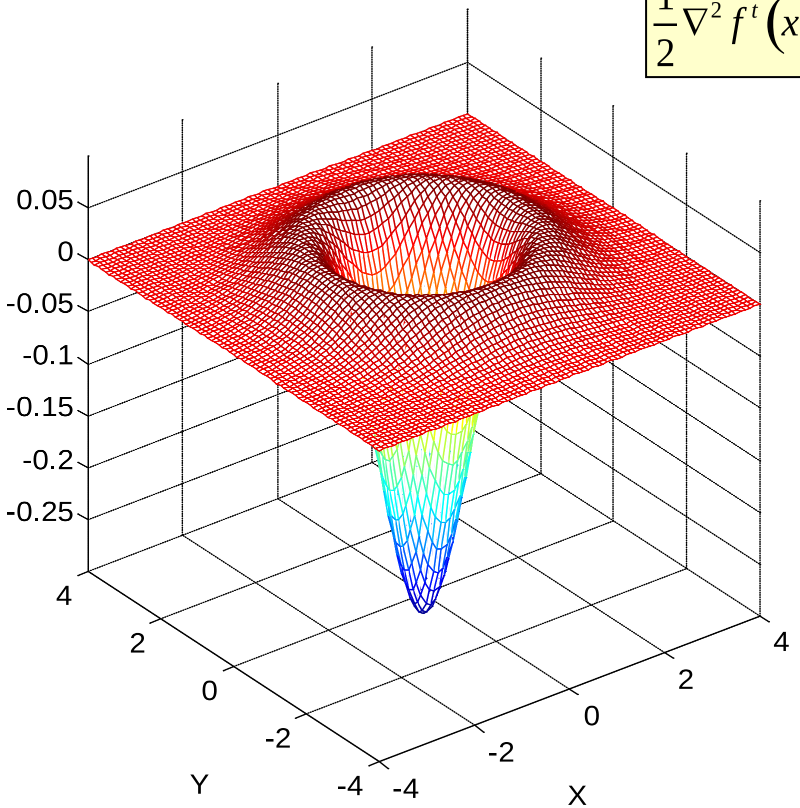
Laplacian of Gaussian

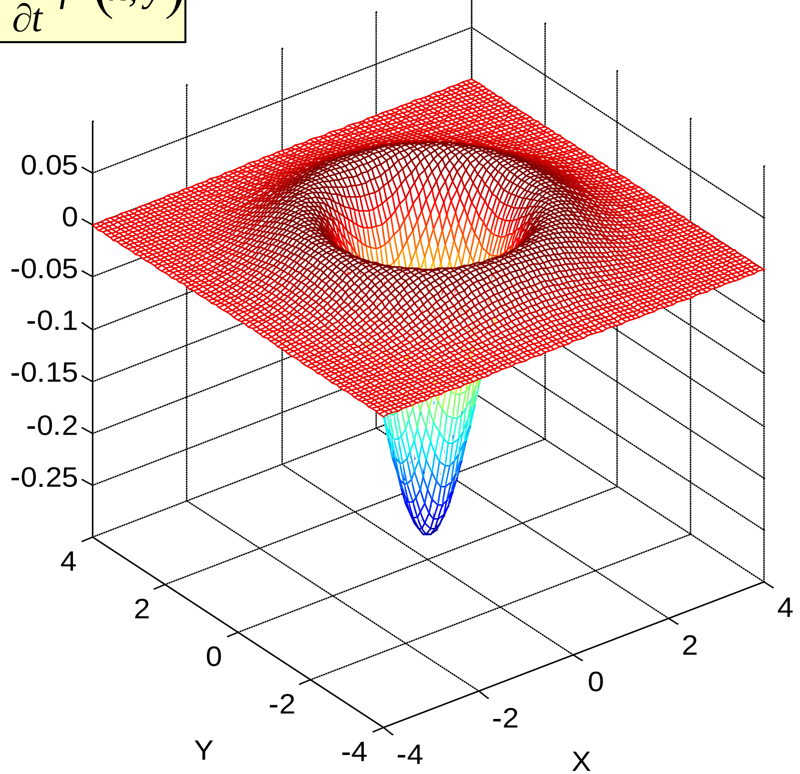
t = σ^2 = 1

$$\frac{1}{2}\nabla^2 f^t(x,y) = \frac{\partial}{\partial t} f^t(x,y)$$

Difference of Gaussians

t = σ^2 = 1, k = 1.1





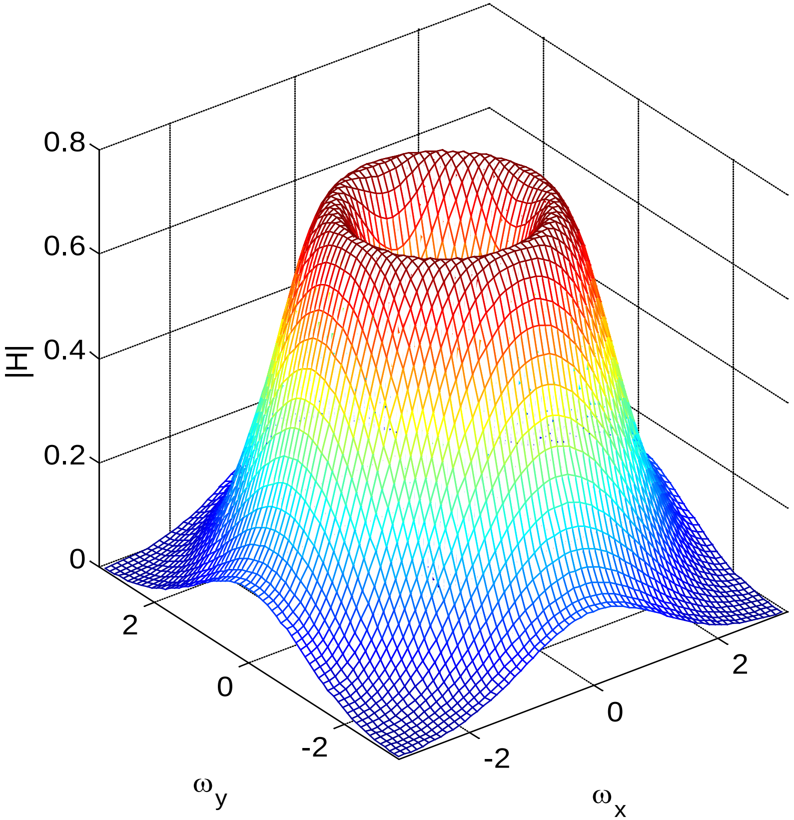
$$LoG(x,y) = -\frac{1}{\pi t^2}\left(1 - \frac{x^2+y^2}{2t}\right) e^{-\frac{x^2+y^2}{2t}}$$

$$DoG(x,y) = \frac{1}{(k-1)t}\left(g^{k^2 t}(x,y) - g^t(x,y)\right)$$

LoG vs. DoG (cont.)

Laplacian of Gaussian

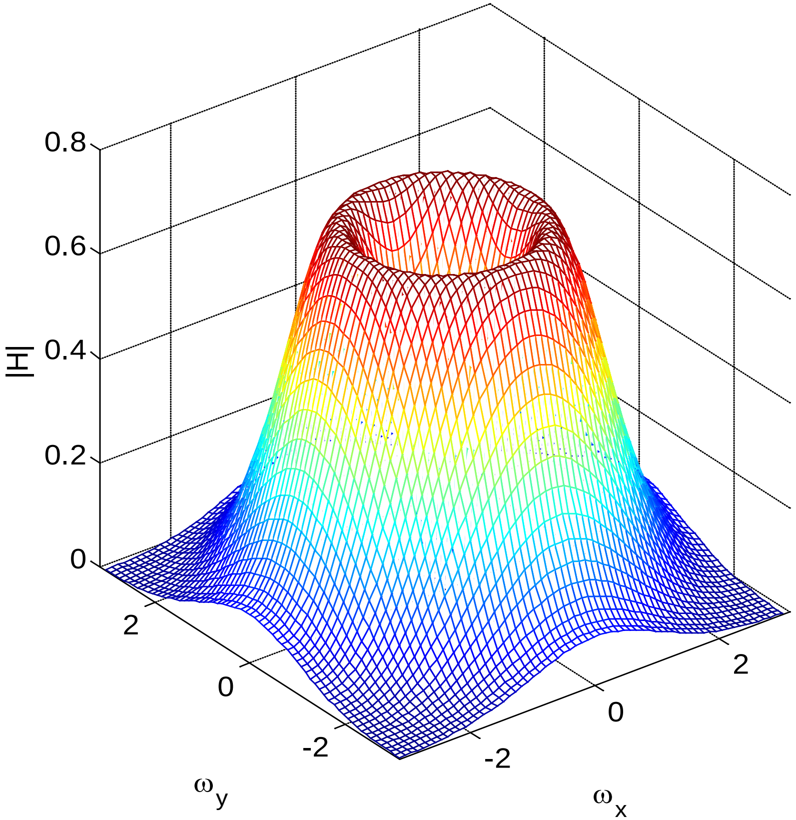
$t = \sigma^2 = 1$



$$H(\omega_x,\omega_y) = -\left(\omega_x^2+\omega_y^2\right)G^t(\omega_x,\omega_y)$$

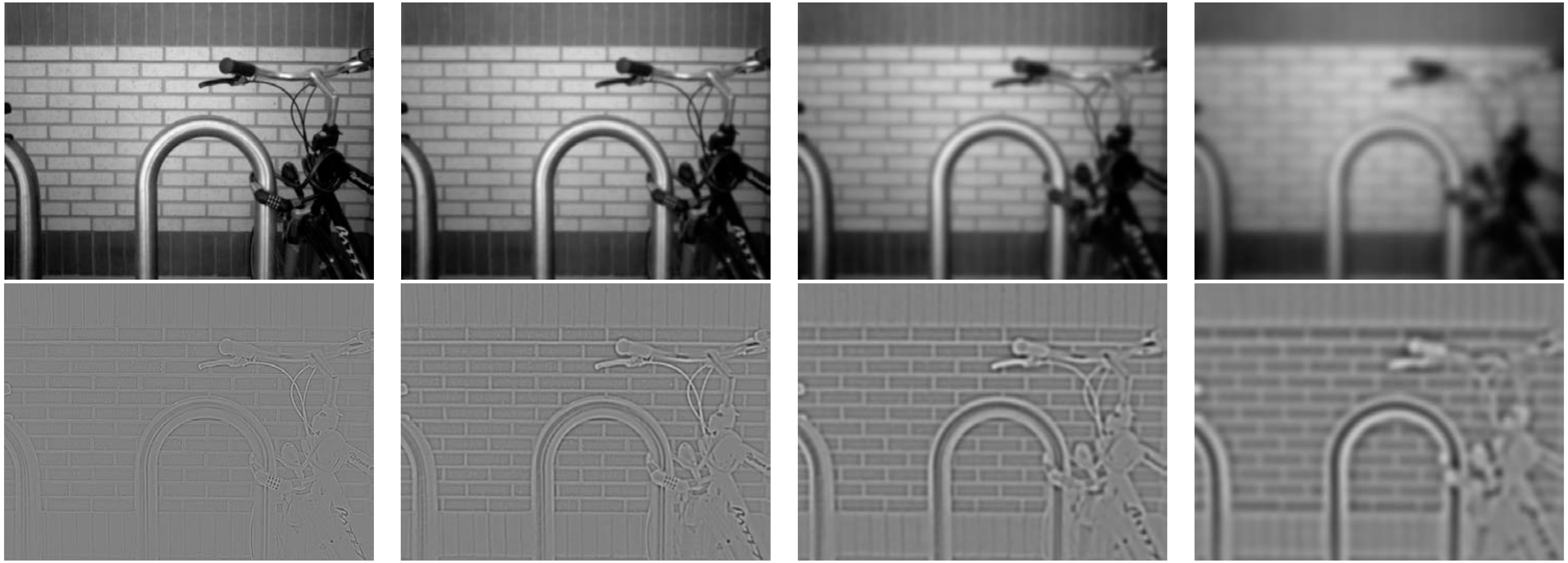
Difference of Gaussians

$t = \sigma^2 = 1, \; k = 1.1$



$$H(\omega_x,\omega_y) = \frac{1}{(k-1)t}\left[G^{k^2t}(\omega_x,\omega_y) - G^t(\omega_x,\omega_y)\right]$$

Scale space: Laplacian images

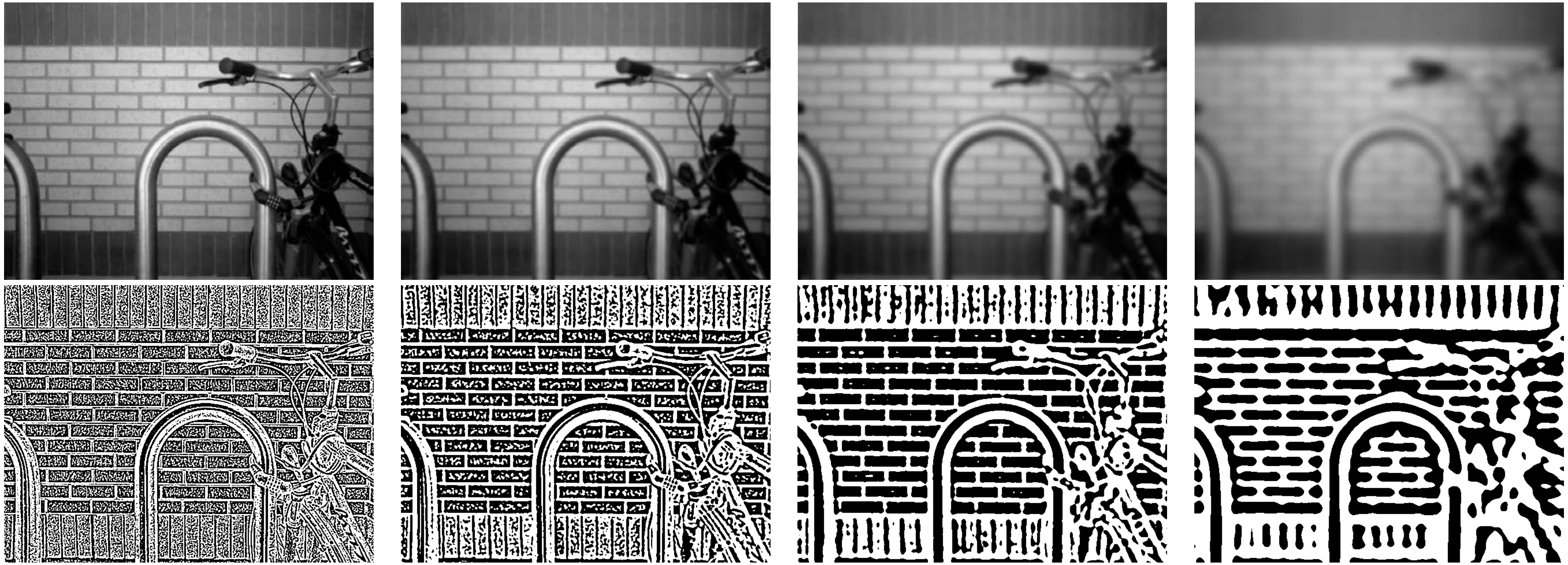


$f^t(x,y)$

$t \cdot \nabla^2 f^t(x,y)$

t = 1 t = 4 t = 16 t = 64

Scale space: Binarized Laplacian images



t = 1 t = 4 t = 16 t = 64