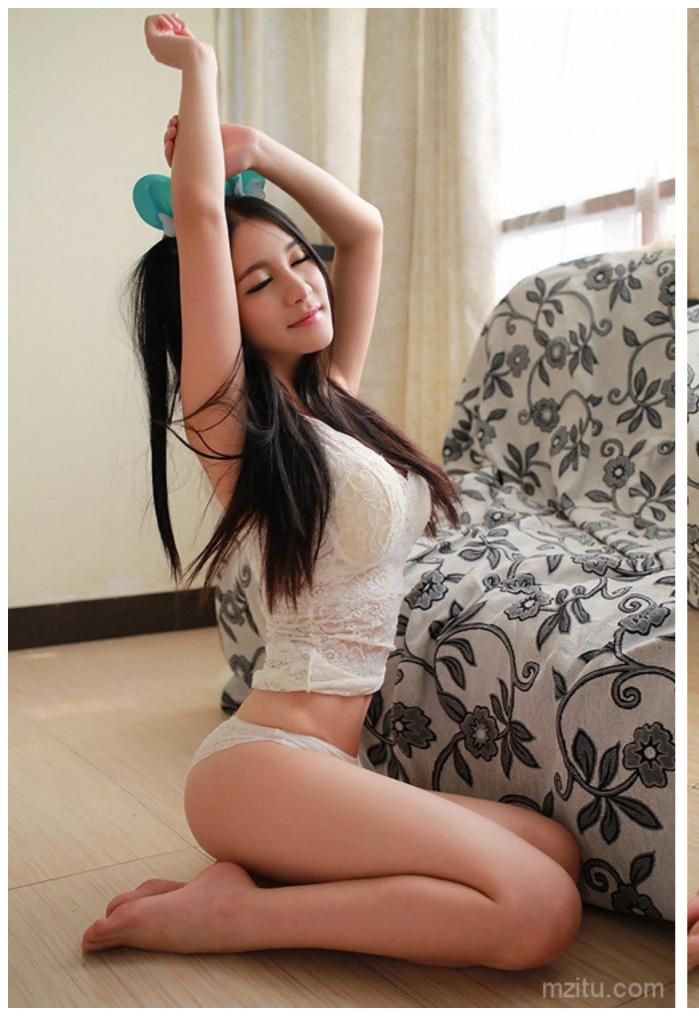
Scale-invariant feature transform

By: 会飞的吴克



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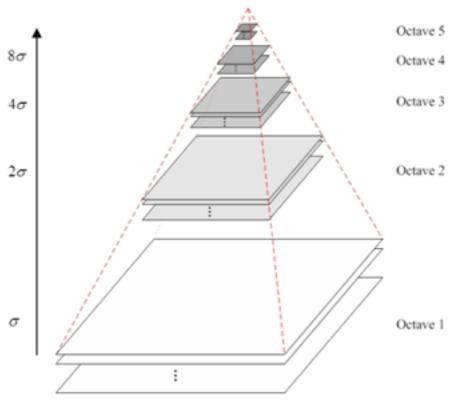


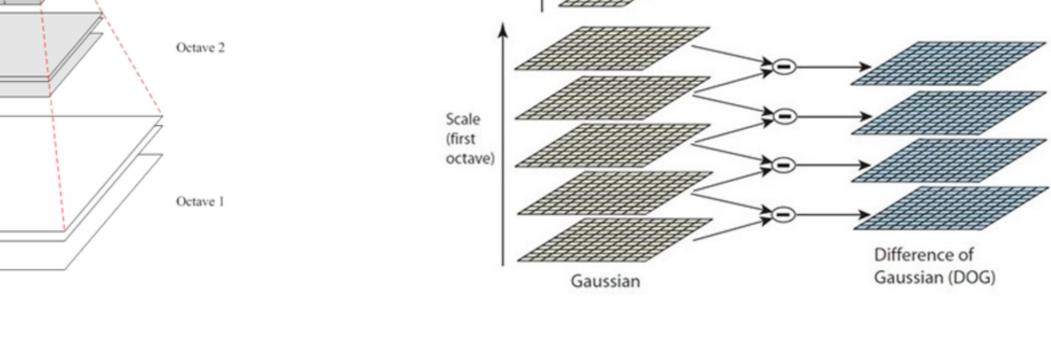






一、建立高斯差分金字塔



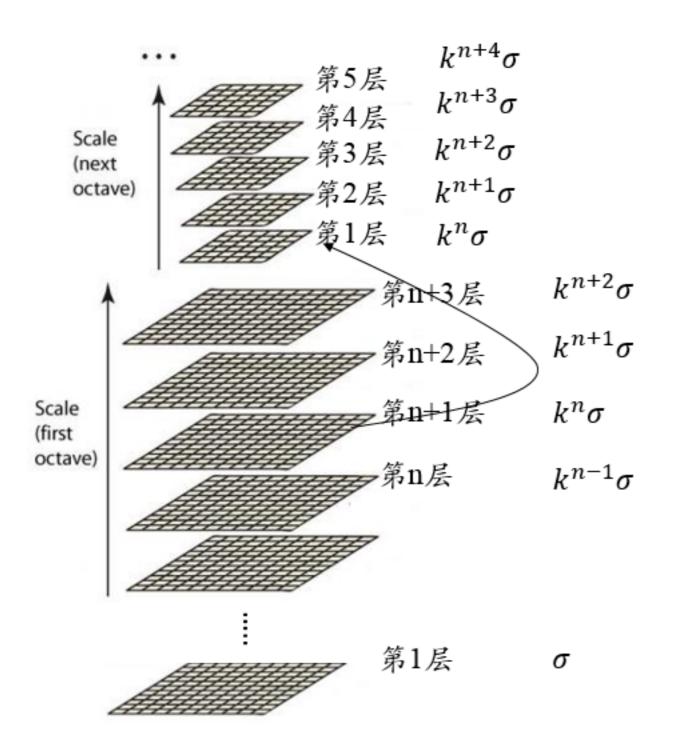


Scale (next

octave)

$$[0 = [\log_2(\min(M, N))] - 3$$

$$S = n + 3$$

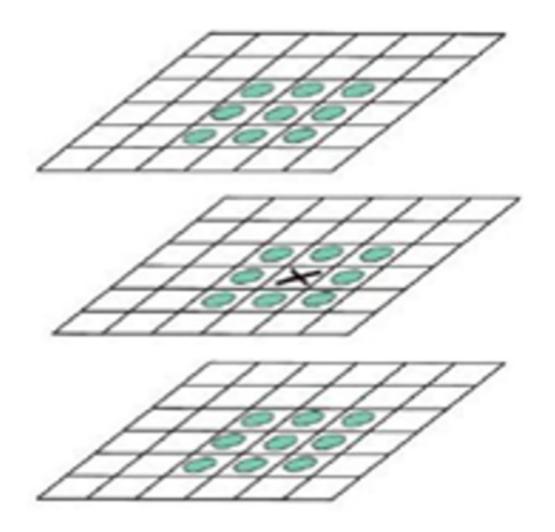


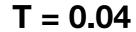
$$k = 2^{1/n}$$

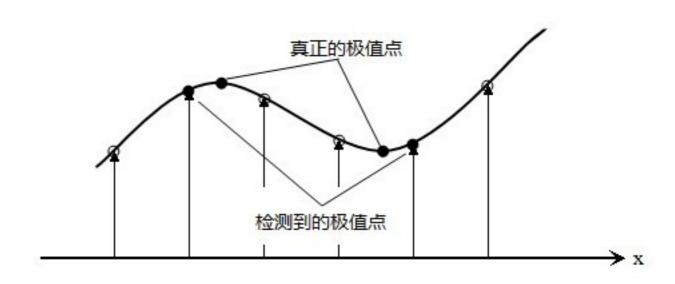
$$\sigma_0 = \sqrt{1.6^2 - 0.5^2} = 1.52$$

- 二、关键点(key points)位置确定
 - 1.阈值化

$$abs(val) > 0.5*T/n$$







3.调整极值点位置

在检测到的极值点*((*,,,,,,,,,,,) 处做三元二阶泰勒展开

$$f\begin{pmatrix} \begin{bmatrix} x \\ y \\ \sigma \end{bmatrix} \end{pmatrix} = f\begin{pmatrix} \begin{bmatrix} x_0 \\ y_0 \\ \sigma_0 \end{bmatrix} \end{pmatrix} + \begin{bmatrix} \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial \sigma} \end{bmatrix} \begin{pmatrix} \begin{bmatrix} x \\ y \\ \sigma \end{bmatrix} - \begin{bmatrix} x_0 \\ y_0 \\ \sigma_0 \end{bmatrix} \end{pmatrix}$$

$$+\frac{1}{2} \begin{bmatrix} x \\ y \\ \sigma \end{bmatrix} - \begin{bmatrix} x_0 \\ y_0 \\ \sigma_0 \end{bmatrix} \end{bmatrix}^T \begin{bmatrix} \frac{\partial^2 f}{\partial x \partial x}, \frac{\partial^2 f}{\partial x \partial y}, \frac{\partial^2 f}{\partial x \partial y}, \frac{\partial^2 f}{\partial x \partial \sigma} \\ \frac{\partial^2 f}{\partial x \partial y}, \frac{\partial^2 f}{\partial y \partial y}, \frac{\partial^2 f}{\partial y \partial \sigma} \\ \frac{\partial^2 f}{\partial x \partial \sigma}, \frac{\partial^2 f}{\partial y \partial \sigma}, \frac{\partial^2 f}{\partial y \partial \sigma}, \frac{\partial^2 f}{\partial \sigma \partial \sigma} \end{bmatrix} \begin{bmatrix} \begin{bmatrix} x \\ y \\ \sigma \end{bmatrix} - \begin{bmatrix} x_0 \\ y_0 \\ \sigma_0 \end{bmatrix} \end{bmatrix}$$

矢量形式:
$$f(X) = f(X_0) + \frac{\partial f^T}{\partial X} \hat{X} + \frac{1}{2} \hat{X}^T \frac{\partial^2 f}{\partial X^2} \hat{X}$$

$$f(\boldsymbol{X}) = f(\boldsymbol{X_0}) + \frac{\partial f^T}{\partial \boldsymbol{X}} \widehat{\boldsymbol{X}} + \frac{1}{2} \widehat{\boldsymbol{X}}^T \frac{\partial^2 f}{\partial \boldsymbol{X}^2} \widehat{\boldsymbol{X}}$$

$$f(x) \dot{\mathcal{R}} = \frac{\partial f(X)}{\partial X} = \frac{\partial f^T}{\partial X} + \frac{1}{2} \left(\frac{\partial^2 f}{\partial X^2} + \frac{\partial^2 f^T}{\partial X^2} \right) \hat{X} = \frac{\partial f^T}{\partial X} + \frac{\partial^2 f}{\partial X^2} \hat{X}$$

令导数为零解得: $\hat{X} = -\frac{\partial^2 f^{-1}}{\partial X^2} \frac{\partial f}{\partial X}$

$$f(\mathbf{X}): f(\mathbf{X}) = f(\mathbf{X}_0) + \frac{\partial f^T}{\partial \mathbf{X}} \widehat{\mathbf{X}} + \frac{1}{2} \left(-\frac{\partial^2 f^{-1}}{\partial \mathbf{X}^2} \frac{\partial f}{\partial \mathbf{X}} \right)^T \frac{\partial^2 f}{\partial \mathbf{X}^2} \left(-\frac{\partial^2 f^{-1}}{\partial \mathbf{X}^2} \frac{\partial f}{\partial \mathbf{X}} \right)$$

$$= f(\mathbf{X}_0) + \frac{\partial f^T}{\partial \mathbf{X}} \widehat{\mathbf{X}} + \frac{1}{2} \frac{\partial f^T}{\partial \mathbf{X}} \frac{\partial^2 f^{-T}}{\partial \mathbf{X}^2} \frac{\partial^2 f^{-1}}{\partial \mathbf{X}^2} \frac{\partial f}{\partial \mathbf{X}}$$

$$= f(\mathbf{X}_0) + \frac{\partial f^T}{\partial \mathbf{X}} \widehat{\mathbf{X}} + \frac{1}{2} \frac{\partial f^T}{\partial \mathbf{X}} \frac{\partial^2 f^{-1}}{\partial \mathbf{X}^2} \frac{\partial f}{\partial \mathbf{X}}$$

$$= f(\mathbf{X}_0) + \frac{\partial f^T}{\partial \mathbf{X}} \widehat{\mathbf{X}} + \frac{1}{2} \frac{\partial f^T}{\partial \mathbf{X}} \left(-\widehat{\mathbf{X}} \right)$$

$$= f(\mathbf{X}_0) + \frac{1}{2} \frac{\partial f^T}{\partial \mathbf{X}} \widehat{\mathbf{X}}$$

还有一些细节问题:迭代次数限制、解超出一定范围舍去

4.舍去低对比度的点

若
$$|f(X)| < \frac{T}{n}$$
 ,则舍去点X

5.边缘效应的去除

$$\boldsymbol{H}(x,y) = \begin{bmatrix} D_{xx}(x,y) & D_{xy}(x,y) \\ D_{xy}(x,y) & D_{yy}(x,y) \end{bmatrix}$$

$$Tr(\mathbf{H}) = D_{xx} + D_{yy} = \alpha + \beta$$

其中:
$$\alpha > \beta$$
: 且 $\alpha = \gamma \beta$

$$Det(\mathbf{H}) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha \beta$$

若 Det(H) < 0 舍去点X

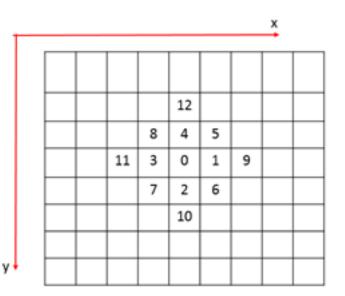
$$\frac{\operatorname{Tr}(\boldsymbol{H})^2}{\operatorname{Det}(\boldsymbol{H})} = \frac{(\alpha + \beta)^2}{\alpha\beta} = \frac{(\gamma\beta + \beta)^2}{\gamma\beta^2} = \frac{(\gamma + 1)^2}{\gamma}$$

若不满足
$$\frac{\operatorname{Tr}(H)}{\operatorname{Det}(H)} < \frac{(\gamma+1)^2}{\gamma}$$
 舍去点X

(建议) 取 10.0)

附:有限差分求导法

$$\left(\frac{\partial f}{\partial x}\right) = \frac{f_1 - f_3}{2h} \tag{1}$$

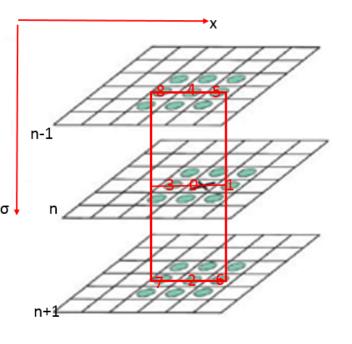


$$\left(\frac{\partial f}{\partial y}\right) = \frac{f_2 - f_4}{2h} \tag{2}$$

$$\left(\frac{\partial^2 f}{\partial x^2}\right) = \frac{f_1 + f_3 - 2f_0}{h^2} \tag{3}$$

$$\left(\frac{\partial^2 f}{\partial y^2}\right) = \frac{f_2 + f_4 - 2f_0}{h^2} \tag{4}$$

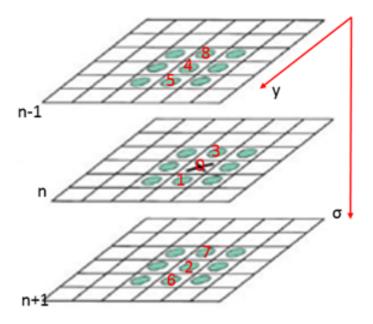
$$\left(\frac{\partial^2 f}{\partial x \partial y}\right) = \frac{\left(f_8 + f_6\right) - \left(f_5 + f_7\right)}{4h^2} \tag{5}$$



$$\left(\frac{\partial f}{\partial \sigma}\right) = \frac{f_2 - f_4}{2h} \tag{6}$$

$$\left(\frac{\partial^2 f}{\partial \sigma^2}\right) = \frac{f_2 + f_4 - 2f_0}{h^2} \tag{7}$$

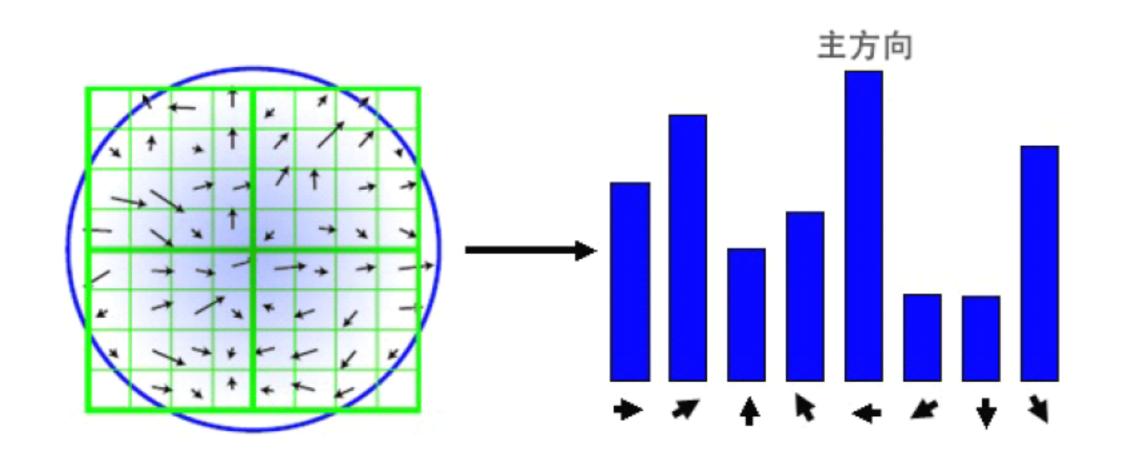
$$\left(\frac{\partial^2 f}{\partial x \partial \sigma}\right) = \frac{\left(f_8 + f_6\right) - \left(f_5 + f_7\right)}{4h^2}$$
(8)



$$\left(\frac{\partial^2 f}{\partial y \partial \sigma}\right) = \frac{\left(f_8 + f_6\right) - \left(f_5 + f_7\right)}{4h^2} \tag{9}$$

三、为关键点赋予方向

统计以特征点为圆心,以该特征点所在的高斯图像的尺度的1.5倍为半径的圆内的所有的像素的梯度方向及其梯度幅值,并做 1.5c 的高斯滤波



(在最接近关键点尺度值σ的高斯图像上进行统计)



四、构建关键点描述符

