中国科学技术大学
University of Science and Technology of China

计算机图形学
Computer Graphics

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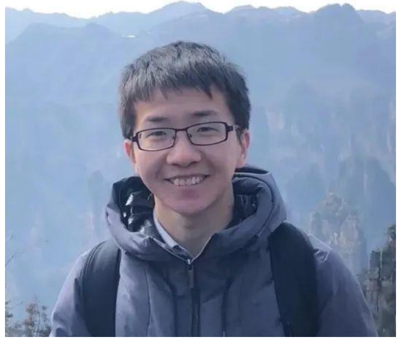
名企大咖面对面(第五季第1期)

一起聊一聊计算机图形学的浪漫

- 2023年3月22日(周三)20:00-21:30
- 中国计算机学会,计算机辅助设计与图形学专委会
- 主题:数字人
  - 百度:百度数字人形象生成和驱动技术前沿进展
  - 凌迪:共创数字未来
  - 黑镜科技:通用数字人技术图谱——建模、驱动、交互、渲染

CAD&CG直播间

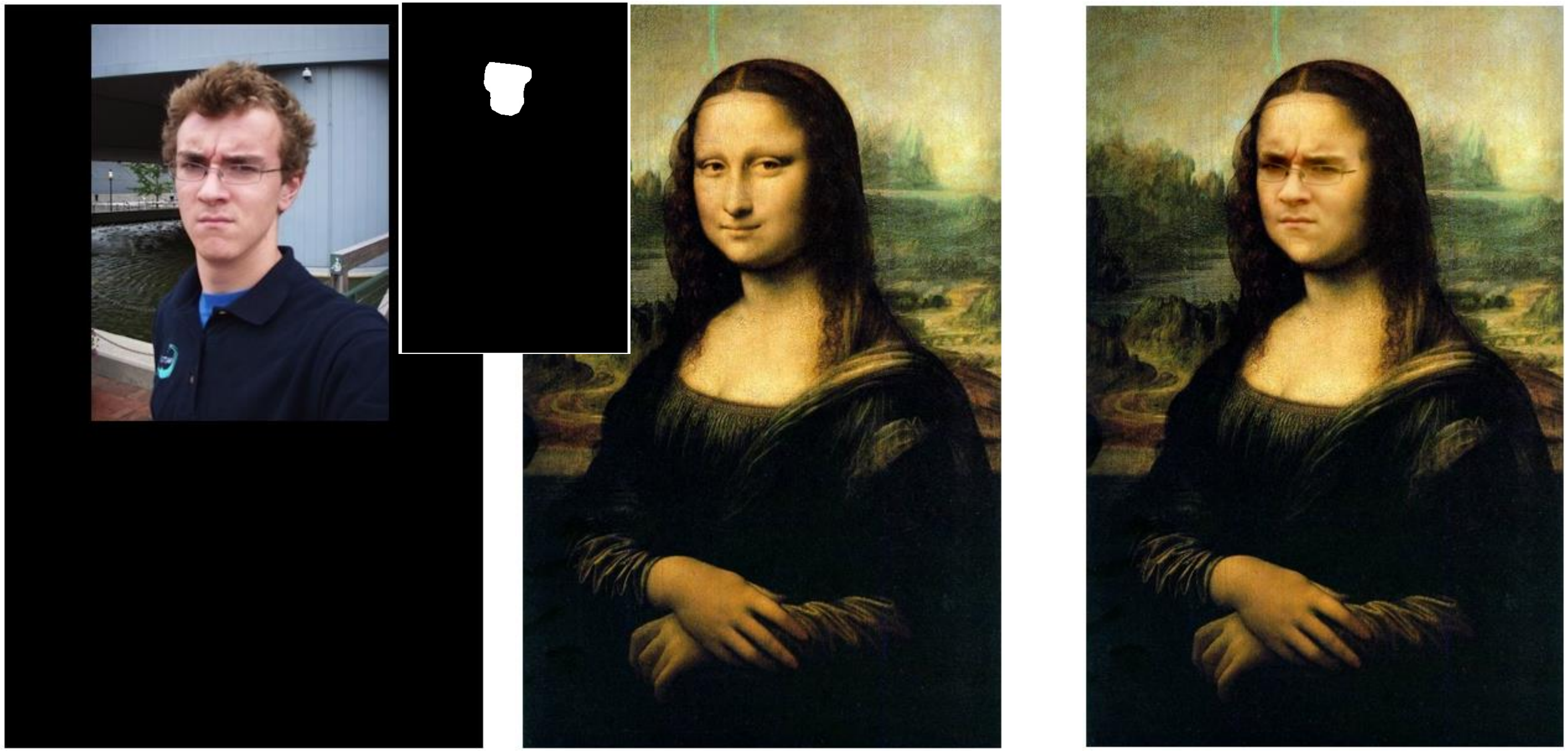

我们是计算机图形学,我们的方向包括:

- 下一代人机交互范式:增强现实
- 支撑吃鸡王者的背后硬核算法
- 解决工业设计领域“卡脖子”问题的计算机辅助设计技术
- 国产自研的数字孪生城市大脑
- 颠覆传统家居设计行业的云平台
- 服务亿万用户的抖音内容创作工具
- 搭载在亿台手机上的图形图像技术
- 工业4.0:智能制造的核心技术3D打印
- 制作精良业内标杆的3A大作
- 国产自主可控的实时渲染引擎

泊松融合

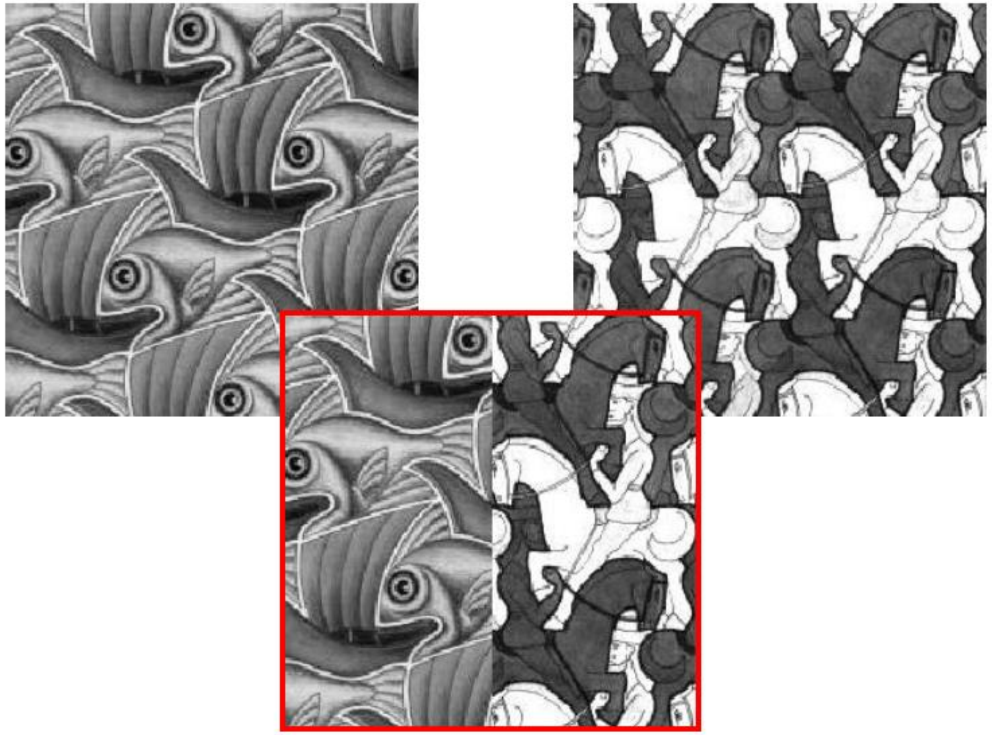
图像融合（Image blending/composition）

- 将图像中提取的对象合成到另外一张图像，生成视觉上自然的新图像

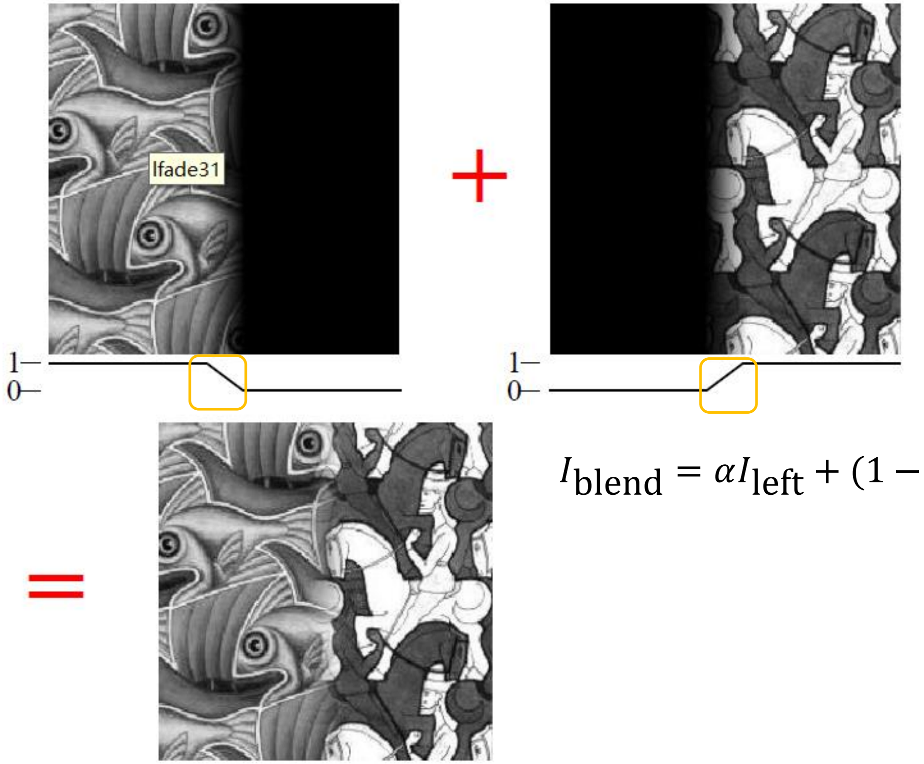


图像融合（Image blending/composition）

- 通过透明度alpha融合，可消除不同图像之间的边界，生成连续的画面



无融合

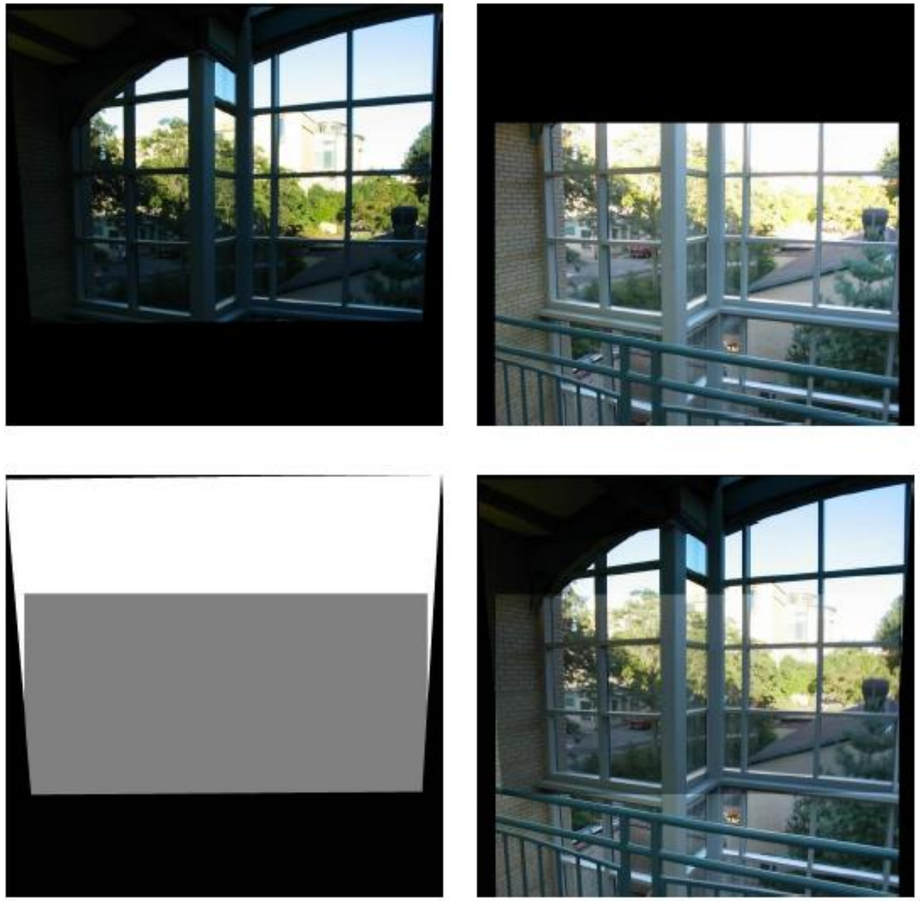


$$I_{\text{blend}} = \alpha I_{\text{left}} + (1-\alpha) I_{\text{right}}$$

透明度融合

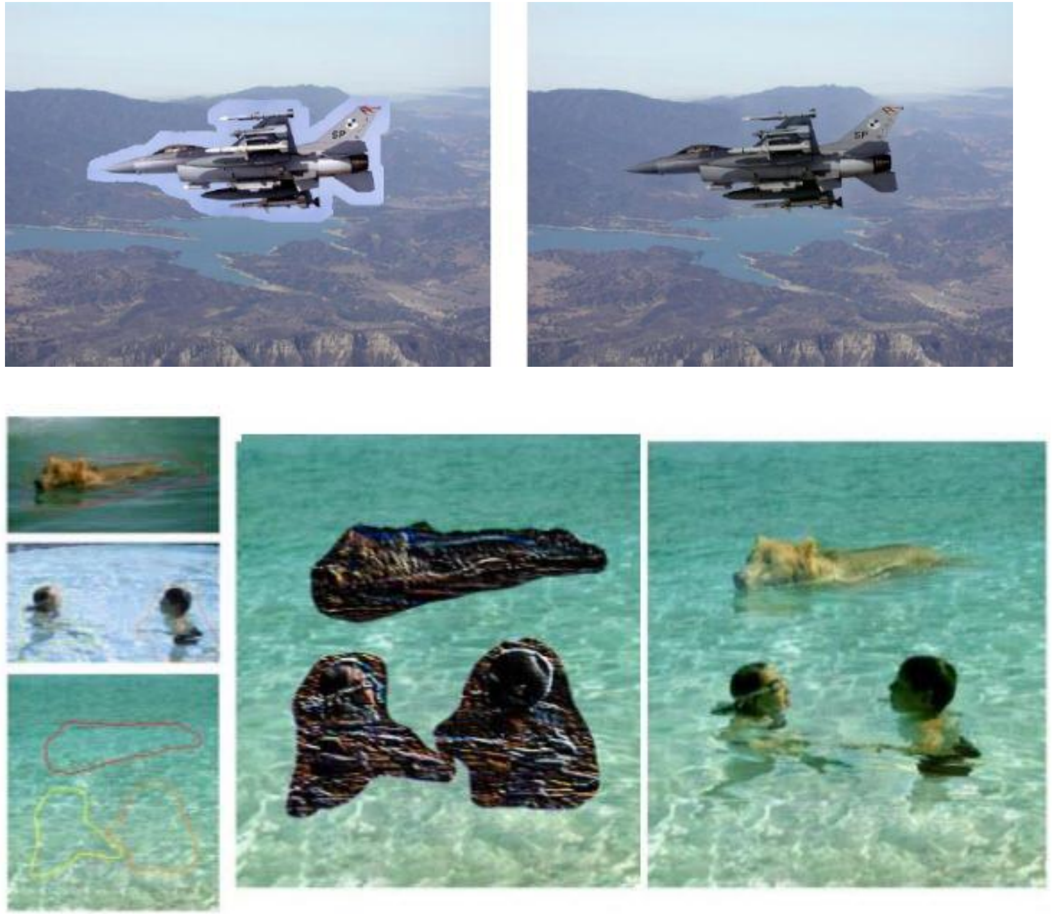
图像融合方式

- 简单透明度融合



$\alpha = 0.5$

- 自适应内容融合



泊松融合

- **思想：** 将原图像的**梯度**嵌入到目标图像
- 根据目标图像的颜色恢复原图像中物体

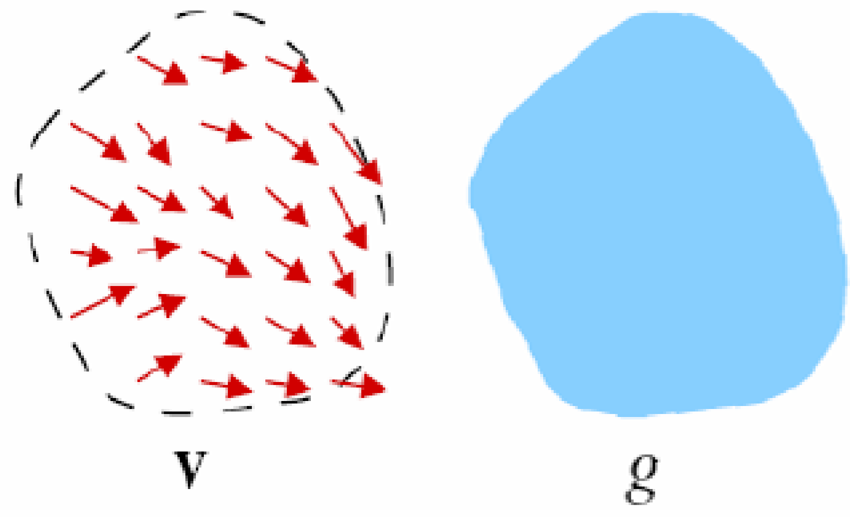
原图像　目标图像　简单融合　泊松融合

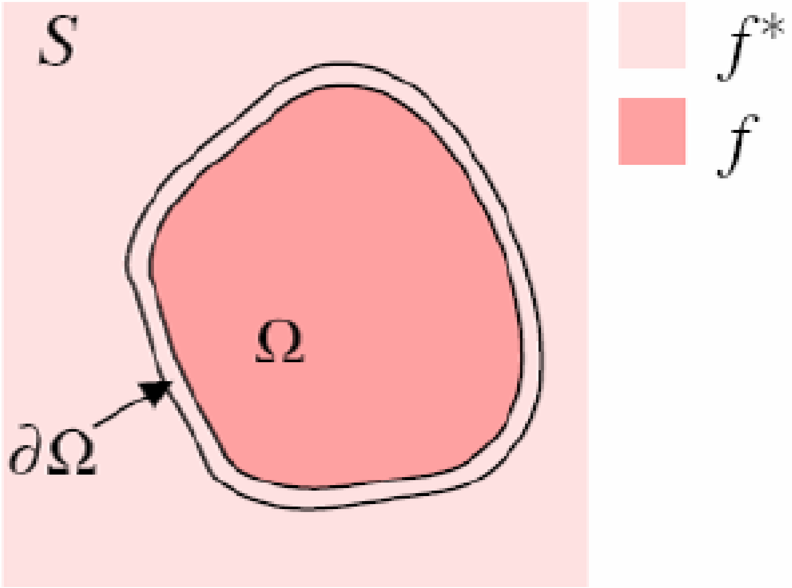
泊松融合

- **方法**
  - 原图像梯度：　$\mathrm{v} = \nabla I = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right)$
  - 目标图像颜色：　$g = f^*$
  - 重叠区域：　Ω

重叠区域融合

$$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right) = \mathrm{v}$$





泊松融合

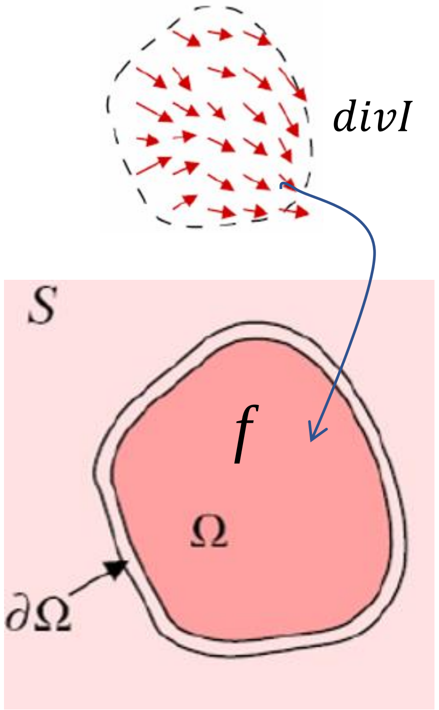
- **方法**：融合函数转化为泊松方程

$$\underset{f}{\operatorname{argmin}} \iint_{\Omega} |\nabla f - \nabla I|^2, \quad s.t. \quad f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

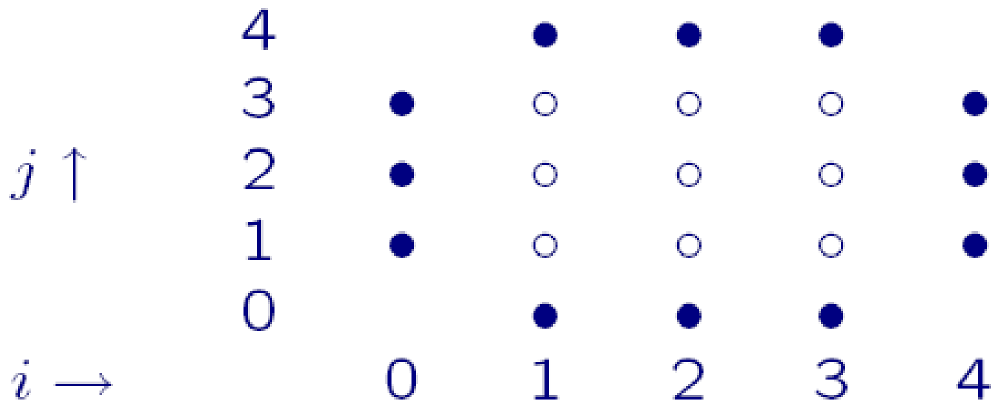
$$\Rightarrow \quad \Delta f = divI \quad s.t. \quad f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

$$\Rightarrow \quad f_{x,y-1} + f_{x-1,y} - 4f_{x,y} + f_{x+1,y} + f_{x,y+1} = divI(x,y)$$

关于融合图像颜色的线性方程组



Discrete Poisson Equation



$$\Delta f = divI(x, y)$$

⇓

$$\frac{f_{i+1,j} + f_{i-1,j} - 2f_{i,j}}{h^2} + \frac{f_{i,j+1} + f_{i,j-1} - 2f_{i,j}}{h^2} = divI(x, y)$$

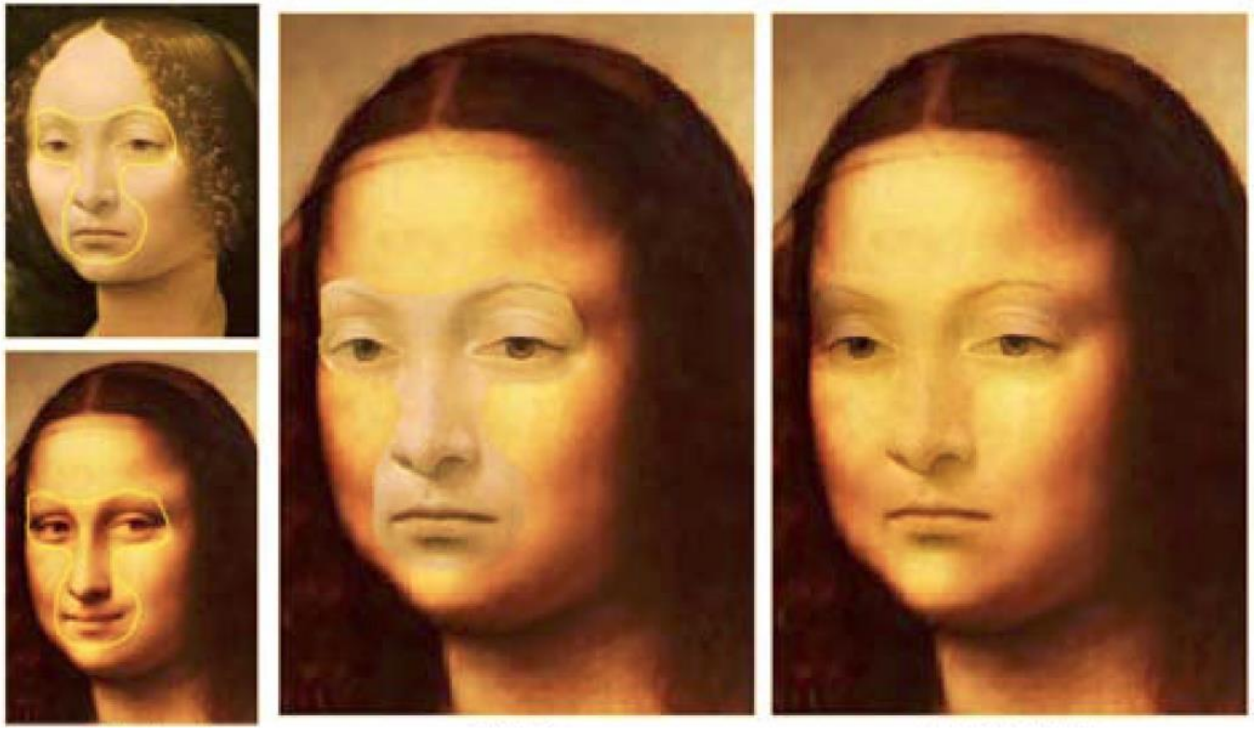
Matrix Nature of Poisson Equation

- Sparse linear system

$$
\begin{bmatrix}
-4 & 1 & & & & & & & \\
1 & -4 & 1 & & & & & & \\
 & 1 & -4 & 1 & & & & & \\
 & & 1 & -4 & 1 & & & & \\
 & & & 1 & -4 & 1 & & & \\
 & & & & 1 & -4 & 1 & & \\
 & & & & & 1 & -4 & 1 & \\
 & & & & & & 1 & -4 & 1 \\
 & & & & & & & 1 & -4
\end{bmatrix}
\begin{bmatrix} f_{11} \\ f_{21} \\ f_{31} \\ f_{12} \\ f_{22} \\ f_{32} \\ f_{13} \\ f_{23} \\ f_{33} \end{bmatrix}
=
\begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{12} \\ b_{22} \\ b_{32} \\ b_{13} \\ b_{23} \\ b_{33} \end{bmatrix}
$$

泊松融合

- 结果



简单融合　泊松融合

可转化为Laplace方程

$$\Delta f = \nabla v \text{ over } \Omega \quad \text{with } f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

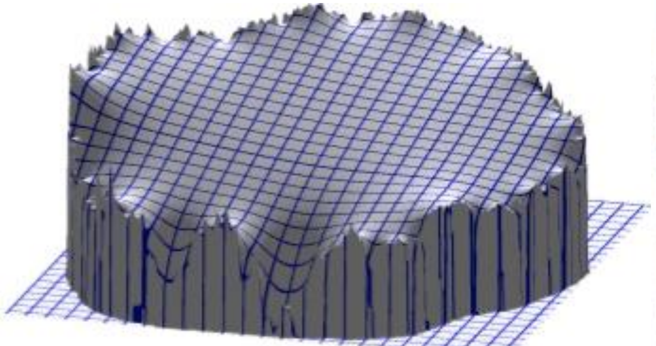
$$\Delta \tilde{f} = 0 \text{ over } \Omega \text{ with } \tilde{f}|_{\partial\Omega} = (f^* - g)|_{\partial\Omega}$$

$$f = g + \tilde{f}$$

基于均值坐标插值的图像融合

- **思想：** 将图像融合转化为给定边界的插值问题，通过插值过程生成融合结果

输入

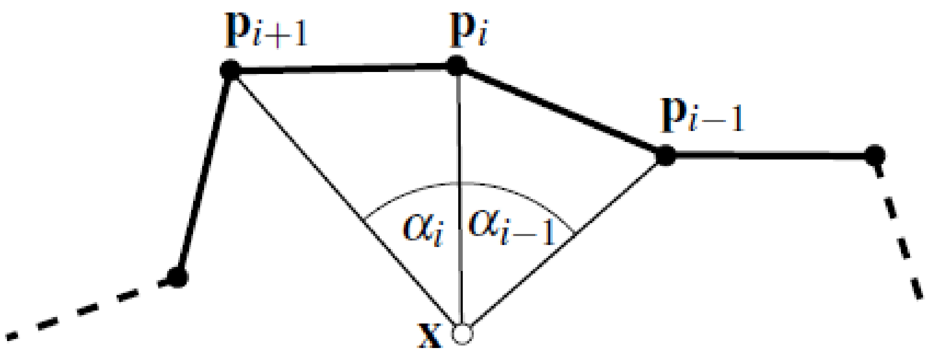


插值函数

融合结果

基于均值坐标插值的图像融合

- **方法:** 多边形均值坐标mean-value coordinates



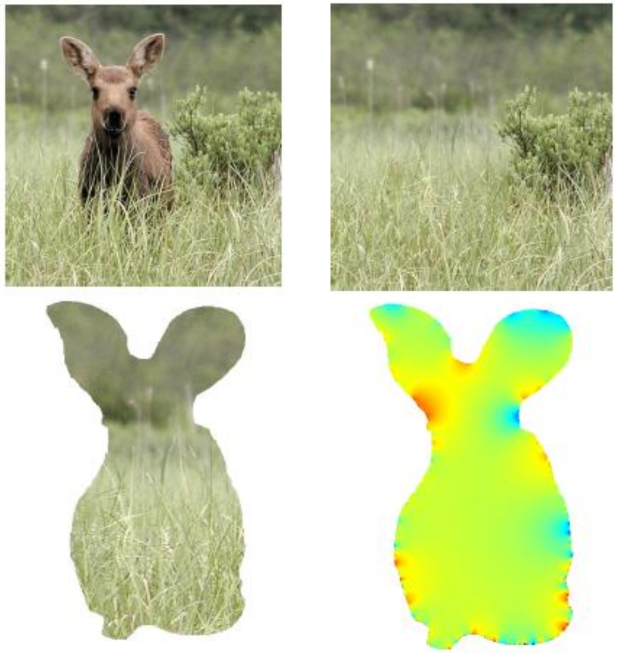
$$\mathbf{x} = \sum_{i=0}^{m-1} \lambda_i(\mathbf{x})\mathbf{p}_i$$

$$\lambda_i(\mathbf{x}) = \frac{w_i}{\sum_{j=0}^{m-1} w_j}$$

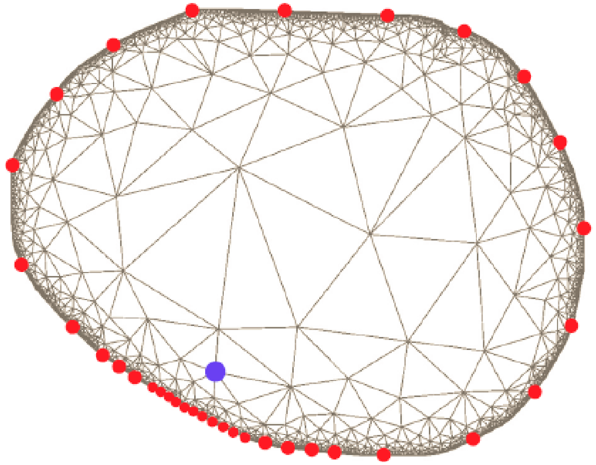
$$w_j = \frac{\tan(\alpha_{i-1}/2) + \tan(\alpha_i/2)}{\|\mathbf{p}_i - \mathbf{x}\|}$$

基于均值坐标插值的图像融合

- **方法**
  - 多边形均值坐标
  - 覆盖区域的边界为多边形进行插值



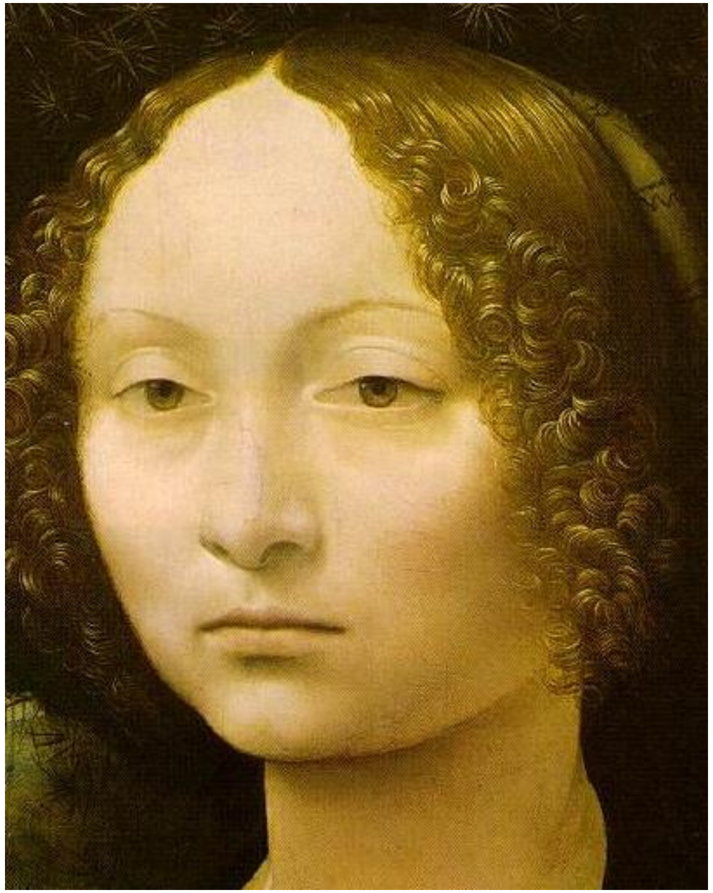
Delaunay三角化加速插值计算

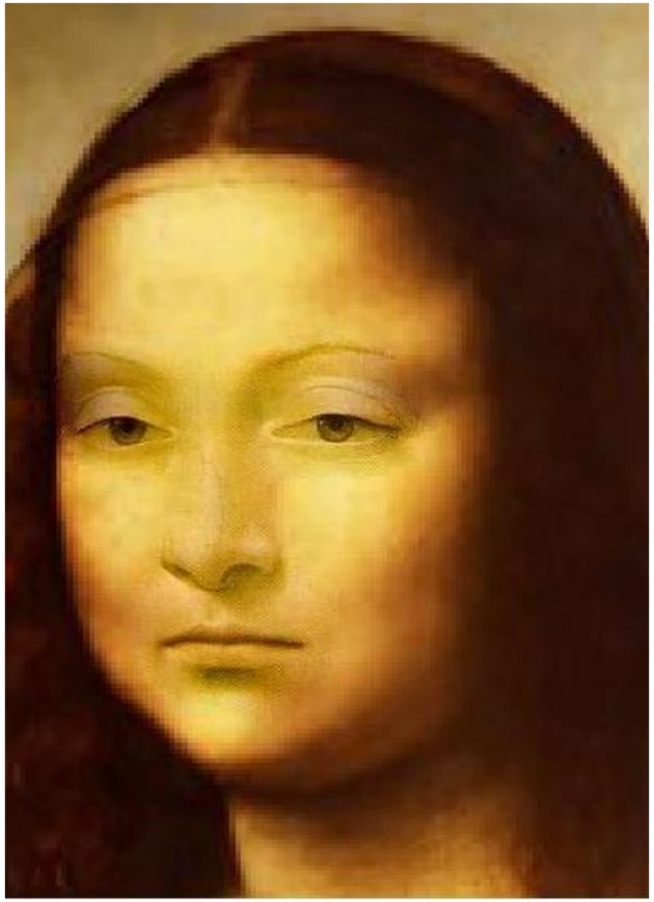


基于均值坐标插值的图像融合

- 结果

泊松融合应用 – change features

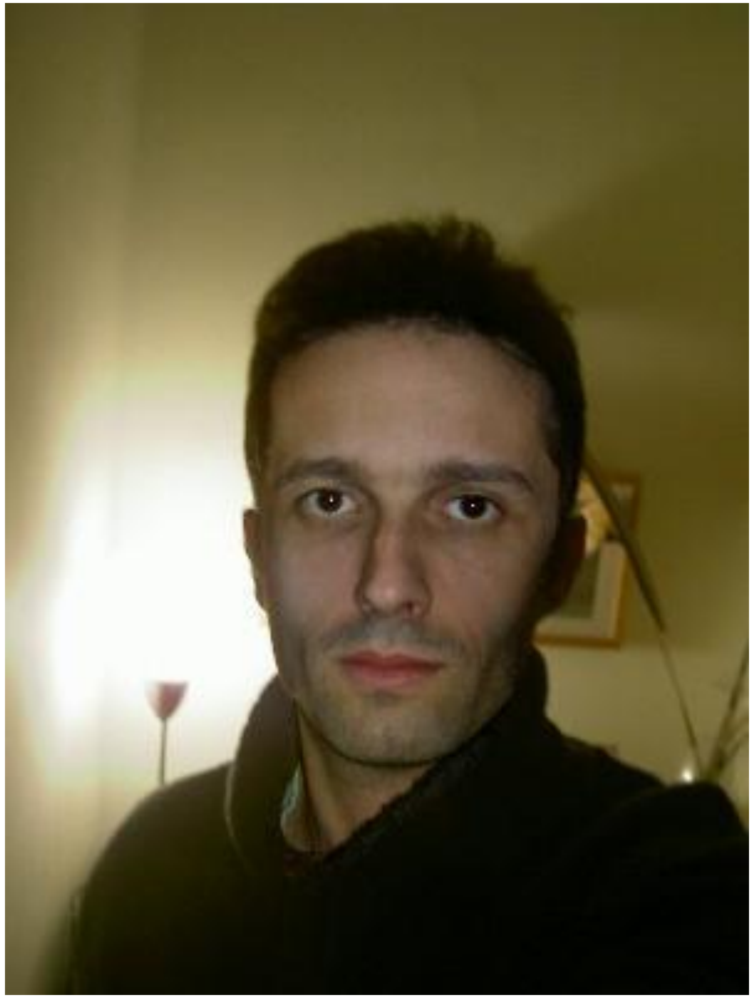




泊松融合应用 – change texture

泊松融合应用 – conceal

泊松融合应用 – mix lights



泊松融合应用 – change colors

泊松融合应用 – change colors

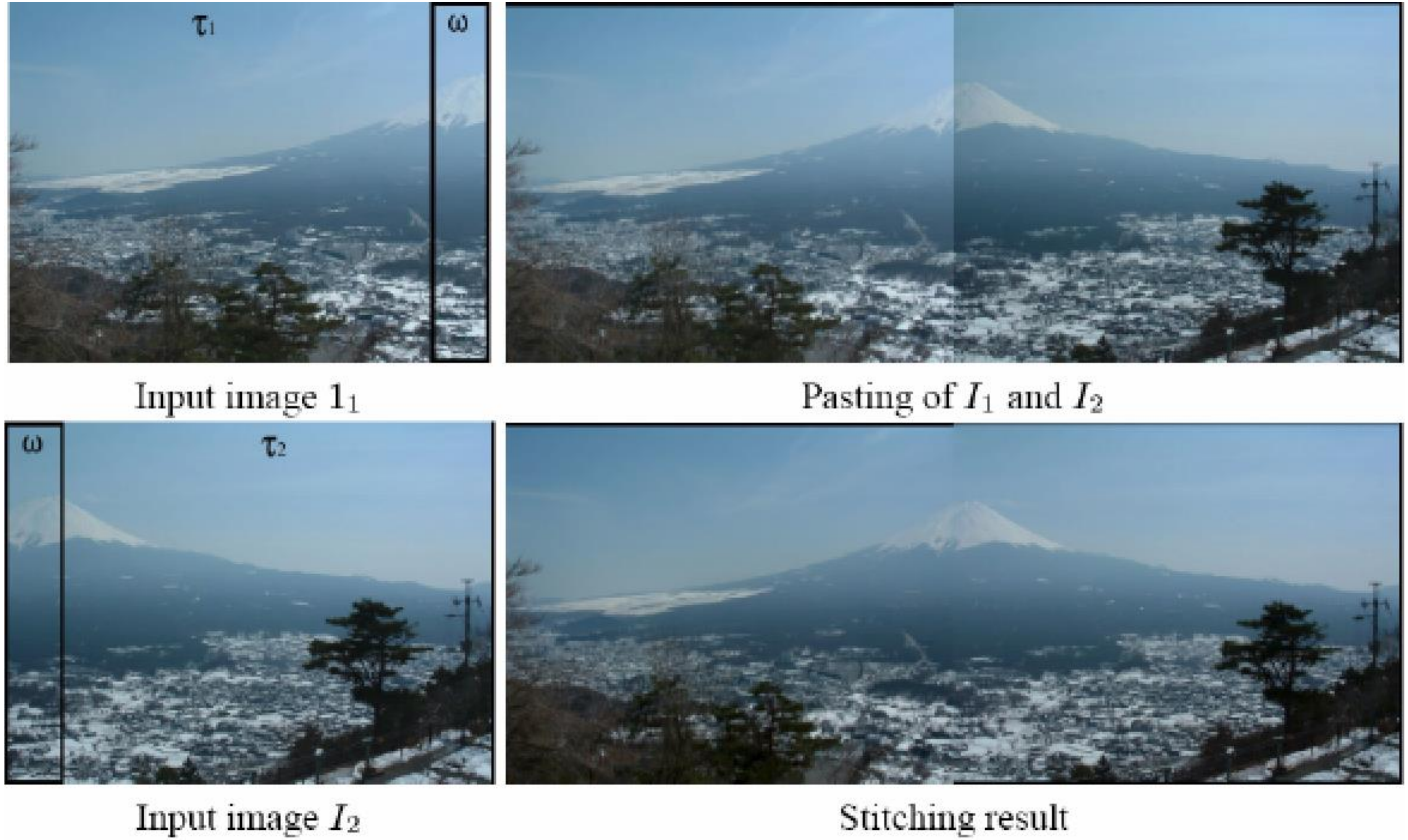
泊松融合应用 – Seamless Tiling

Single image

泊松融合应用 – Seamless Tiling

Multiple images tiled at random

泊松融合应用 – Image Stitching



Poisson Equation

$$\Delta\Phi = -4\pi G\rho(x, y)$$

$$\Delta \equiv \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$$

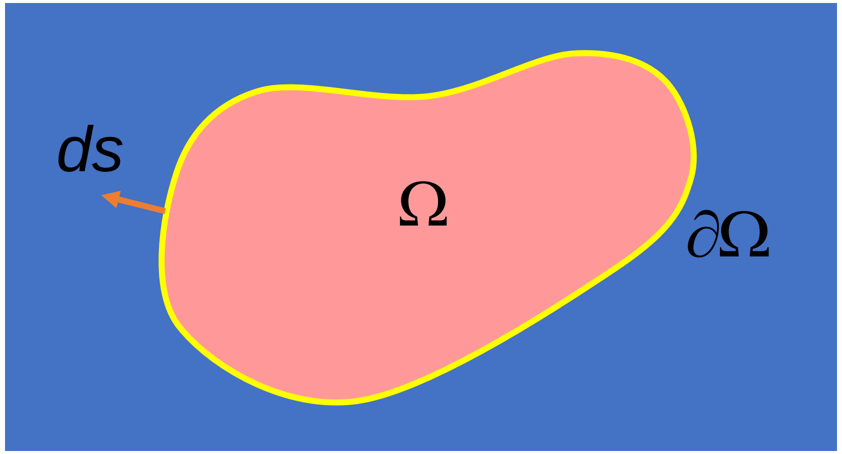
Boundary conditions

- *Dirichlet* boundary conditions:

$$f\,|_{\partial\Omega}$$

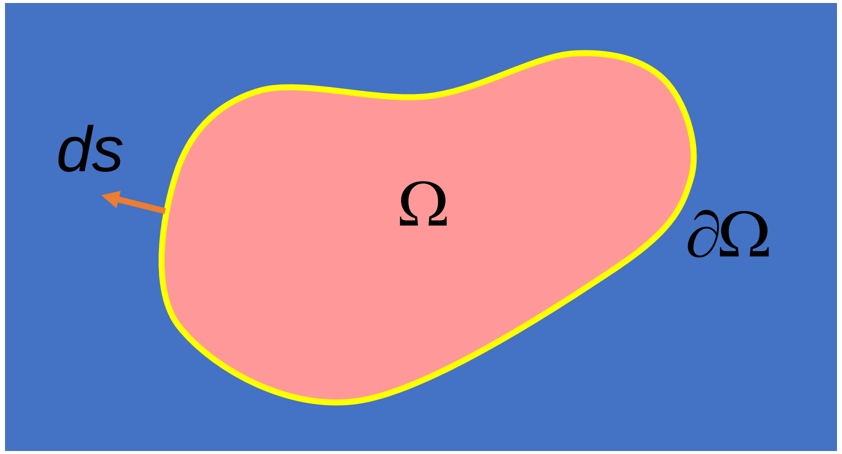
- *Neumann* boundary conditions:

$$\frac{\partial f}{\partial \mathbf{s}}\,|_{\partial\Omega}$$



Existence of solution

The solution of an Poisson Equation is uniquely determined in Ω , if *Dirichlet* boundary conditions or *Neumann* boundary conditions are specified on $\partial\Omega$



Variational interpretation

$$f^* = \arg\min_f \iint_\Omega \underbrace{\|\nabla f - \mathbf{v}\|^2}_{F} \quad \text{s.t } f^*|_{\partial\Omega} = f|_{\partial\Omega}$$

Euler Equation: $F_f - \frac{\partial}{\partial x} F_{f_x} - \frac{\partial}{\partial y} F_{f_y} = 0$

$$\Delta f = div(\mathbf{v}) \quad \text{s.t } f^*|_{\partial\Omega} = f|_{\partial\Omega}$$

$\mathbf{v}$ is a guidance field, needs not to be a gradient field.

Thank you!

Questions?