Poisson Matting(ID: 25)

Github link :

https://github.com/Digital-Image-Processing-IIITH/project-made-online

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Main Goal :

Matting for natural images in complex scenes by calculating the gradient of matte from image and solving Poisson equations.

Problem Definition :

Image Matting in a natural image setting involving complex scenes is a challenging problem. We tackle it using a semi-automatic approach relying on approximate matte from an image gradient given a user-supplied trimap. We formulate the problem as Poisson matting: where the gradient matte field is approximated from image and image matte is solved using poison equations. We use global Poisson matting, a semi-automatic approach to approximate matte from an image gradient given a user-supplied trimap. Global poisson matting fails to generate a good matte in complex scenes. To combat it we introduce local Poison matting and manipulate the continuous gradient field in a local region. The image gradients are visually distinguishable in local regions and thus user's knowledge in the local gradient field can be exploited to get better mattes.

Image matting

Image matting in our setting refers to foreground extraction from any given image.

A new image can be blended from a background image and foreground image with its "alpha matte".

New image: $I = \alpha(x, y)F(x, y) + (1 - \alpha)B(x, y)$ –– (1)

where $\alpha(x,y)$ is the alpha matte of the given image, F(x,y) is the foreground image and B(x,y) is the background image.

In natural image matting α, F and B need to be estimated.

Poisson matting

We tackle the problem of natural image matting of complex scenes by solving Poisson equations with the matte gradient field. Poisson matting generates good matting results on complex scenes which are not possible with conventional matting technique.

Steps:

1. **Approximating the gradient field of matte from the input image**

   In order to do so we take partial derivative on both sides of eq(i)

$$\nabla I = (F - B)\nabla\alpha + \alpha\nabla F + (1 - \alpha)\nabla B \quad \text{––} \ (2)$$

Where $\nabla = (\frac{\partial}{\partial x}, \frac{\partial}{\partial y})$

   Equation (2) is taken for R, G, B channels separately.

   When the foreground and background are smooth, the gradient field can be approximated

$$\nabla\alpha \approx \frac{1}{F - B}\nabla I \quad \text{––} \ (3)$$

2. Reconstructing matte by solving poisson equations

Equation (3) shows that matte gradient is proportional to the image gradient. Thus the matte can be reconstructed efficiently in 2D image space by solving poisson equations.

Global poisson matting

The image is divided into three regions: definitely foreground Ω_F, definitely background Ω_B and "unknown" Ω. To recover matte for the unknown region, we minimize the following equation:

$$\alpha^* = \arg\min_{\alpha} \int\int_{p\in\Omega} ||\nabla\alpha_p - \frac{1}{F_p - B_p}\nabla I_p||^2 dp$$

This is an Iterative optimization process as follows:

1. *(F - B) Initialization* : For each pixel in Ω, F and B are approximated by corresponding to nearest pixels in Ω_F and Ω_B. The (F - B) image is then smoothened by a Gaussian filter.
2. α reconstruction : by solving the Poisson equation using current (F - B) and ∇I.
3. F, B refinement : Let $\Omega^+_F = \{p \in \Omega | \alpha_p > 0.95, I_p \approx F_p\}$ and $\Omega^+_B = \{p \in \Omega | \alpha_p < 0.05, I_p \approx B_p\}$. Update F_p and B_p according to the color of nearest pixel in $\Omega_F \cup \Omega^+_F$ and in $\Omega_B \cup \Omega^+_B$.

Steps 2 and 3 are iterated until the change is sufficiently small.

Local Poisson matting:

Equation (2) can be rewritten as:

$$\nabla\alpha = A(\nabla I - \mathbf{D}) \qquad (7)$$

$A = \frac{1}{F-B}$ and $\mathbf{D} = [\alpha\nabla F + (1-\alpha)\nabla B]$. A

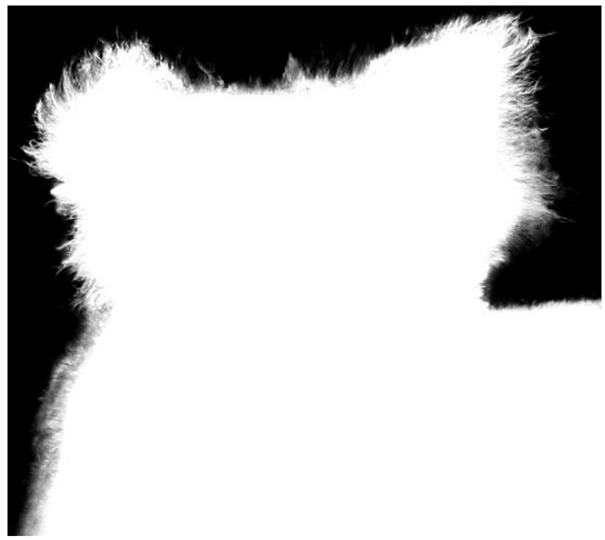
A affects the matte gradient scale in that increasing **A** would sharpen boundaries. **D** is a gradient field caused by the background and foreground. Hence,we need to estimate **A** and **D** to approach the ground truth, **A*** and **D***

When the background or foreground have strong gradients, global Poisson matting results in a poor quality matte. A few techniques have been developed to solve this. They are:

1. **Poisson Matting in Local Region -** Applying a Poisson Matte in regions the user is not satisfied.
2. **Local Operations**
    a. Channel Selection
    b. Local Filtering
    c. Refinement Process

Results

- We thus expect to generate a high quality image matte as shown in b). This matte can then be used to change the background of the image as shown in b, c.

a) Original Image b)Matte generated using Poisson Matting


c) image with extracted koala and constant-colour background d) Image with a new background

Applications:

Changing Backgrounds of complex natural images

We can change the background of any image using our high quality matte generated by poisson matting.

Multi-background

Poisson matting can be applied to matting with multiple backgrounds by calculating the mean image of all backgrounds. Suppose we have T images I. The mean image is calculated as:

$$\bar{I} = \frac{1}{T}\sum_{t}^{T}(\alpha F + (1-\alpha)B_t) = \alpha F + (1-\alpha)\overline{B}$$

where B_t is Background of t^{th} image.

We expect poison matting to work better on multiple backgrounds.

De-fogging (Implementation as a part of this project is tentative)

The above images show the de-fogging done on an image using Poisson matting.

Milestones and Expected Timeline :

Expected to complete by	Topics
31st October	Global Poisson Matting
12th November	Local Poisson Matting
18th November	Integration and testing, final deliverable

Dataset Details :

Natural images captured by smartphone camera by us.

No explicit dataset required for the problem.