# Poisson Matting (ID:25)

Team: MADE ONLINE
Mentor : Prajwal Krishna Maitin

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

# CONTENTS

# GOALS

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- Matting for natural images in complex scenes by calculating the gradient of matte from image.
- Solving Poisson equation.
- Integrating user's knowledge and calculating matte in semi-supervised way(global and local matting)

# IMAGE MATTING

Image matting involves the following steps:

1. Image matting in our setting refers to foreground extraction from any given image.
2. A new image can be blended from a background image and foreground image with its "alpha matte".
3. $I = \alpha F + (1 - \alpha) B$ where F is the foreground, B is the new background and alpha is the matte calculated

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

# GLOBAL MATTING

# STEPS INVOLVED

Global matting involves the following steps:

1. Find approximate foreground and background using an alpha.
2. Find the Poisson Equation for this image.

$$\Delta\alpha = div\left(\frac{\nabla I}{F - B}\right)$$

where, $\Delta = \left(\frac{\partial^2}{\partial x^2}, \frac{\partial^2}{\partial y^2}\right)$ is Laplacian Operator and div is divergence opertor

# STEPS INVOLVED

3. Apply the following Gauss Seidel Iteration to find a good approximate for alpha.

Given,

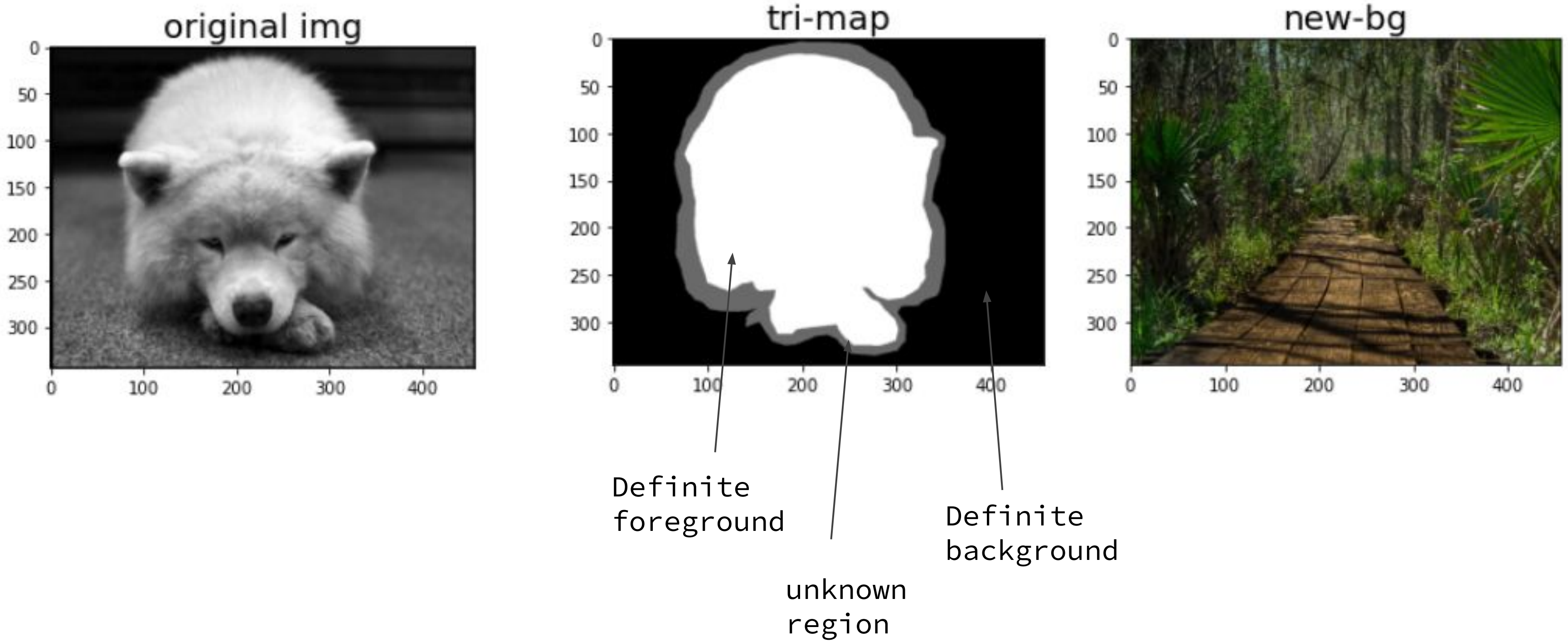
$$\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} = S$$

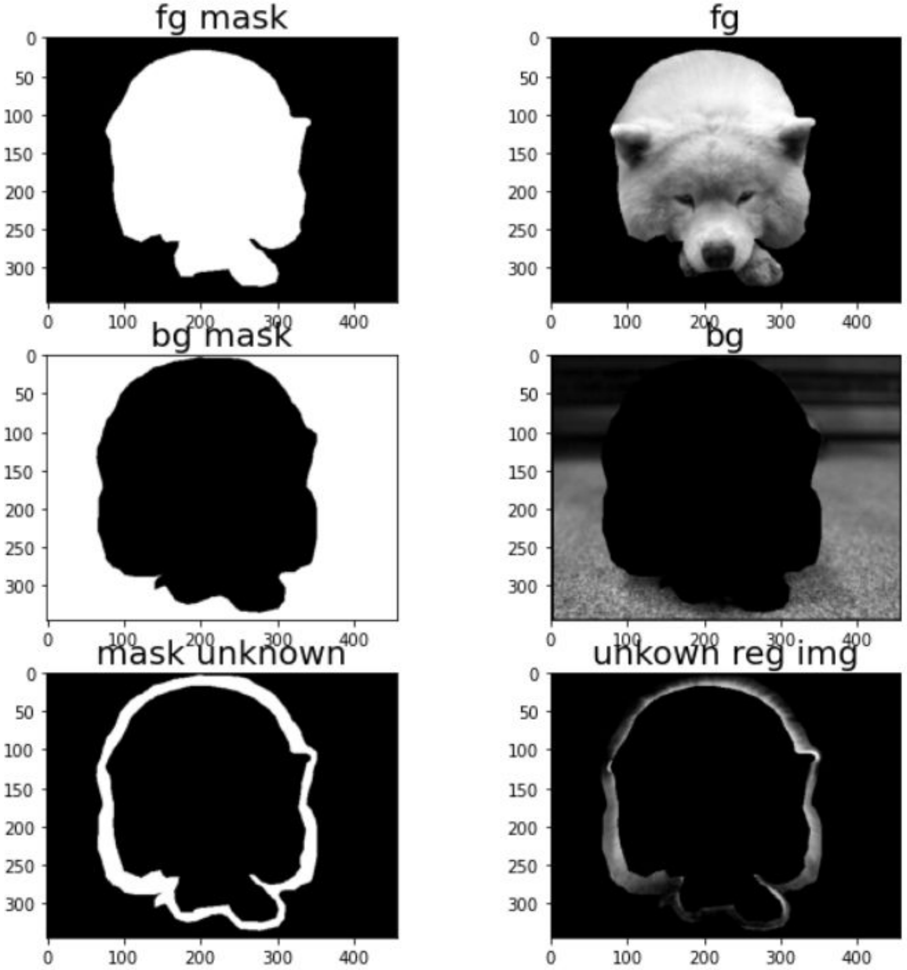
$$f_{i,j}{}^{(n+1)} = \frac{\beta}{4}(f_{i+1,j}{}^{(n)} + f_{i-1,j}{}^{(n+1)}) + f_{i,j+1}{}^{(n)} + f_{i,j-1}{}^{(n+1)} - S_{i,j}) + (1-\beta)f_{i,j}{}^{(n)}$$

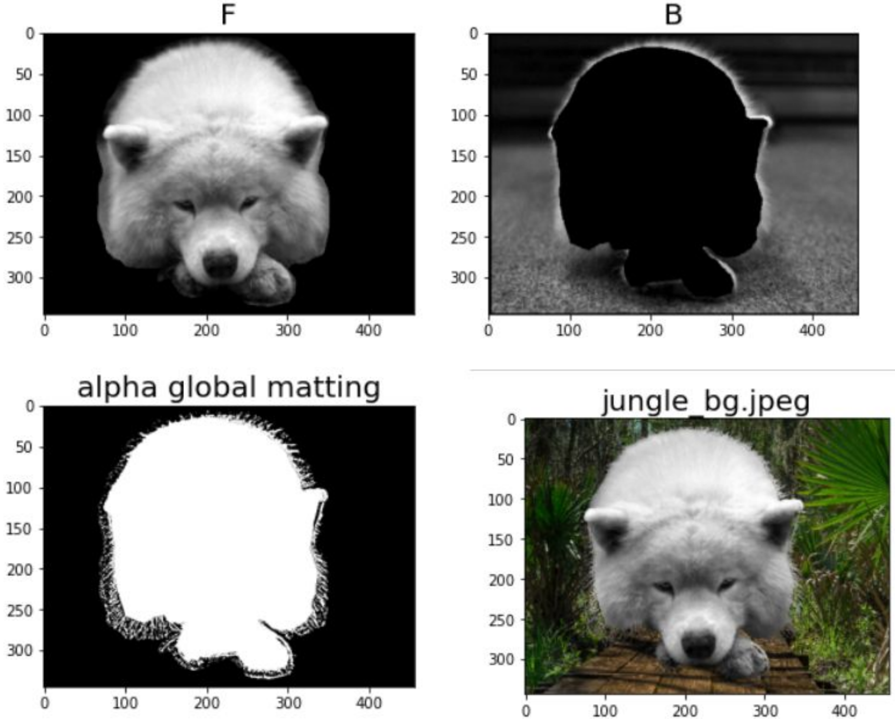
where, $\beta$ lies in the range (1,2)

4. Use this alpha to get the final new image.

# Working of global matting (inputs)



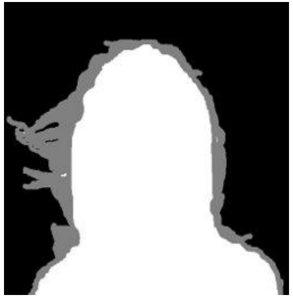



working of Global matting

(Outputs)

Image



Trimap

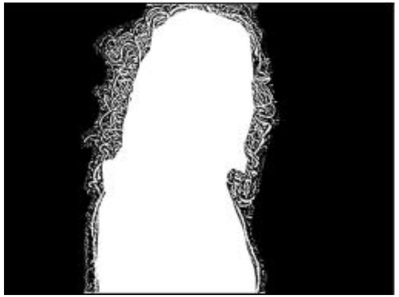
Estimate
Matte

New
Background

Image with
new bg

Image

Trimap



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Matte

New
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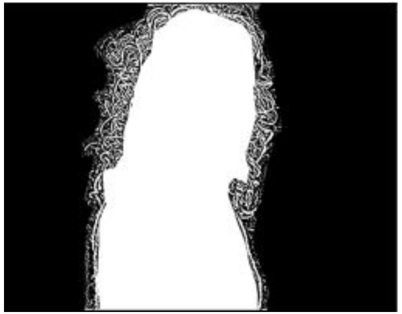
Image

Trimap



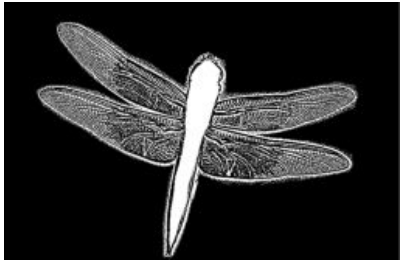
Estimate
Matte

New
Background

Image with
new bg

Image

Trimap



Estimate
Matte

New
Background

Image with
new bg

# LOCAL MATTING

# Poisson Matting in Local Region

- To refine the result of poisson matting, the user can select regions to improve the matte.
- This is needed when the background/foreground is complex and the assumption $\alpha \nabla F + (1 - \alpha) \nabla B \approx 0$ fails.
- Hence now we have to solve this new poisson equation

$$\nabla \alpha = \frac{1}{F - B} (\nabla I - \alpha \nabla F - (1 - \alpha) \nabla B)$$

Where F and B are initial foreground and background image and α is alpha estimated from global matting.

# Local Matting by solving Poisson equation

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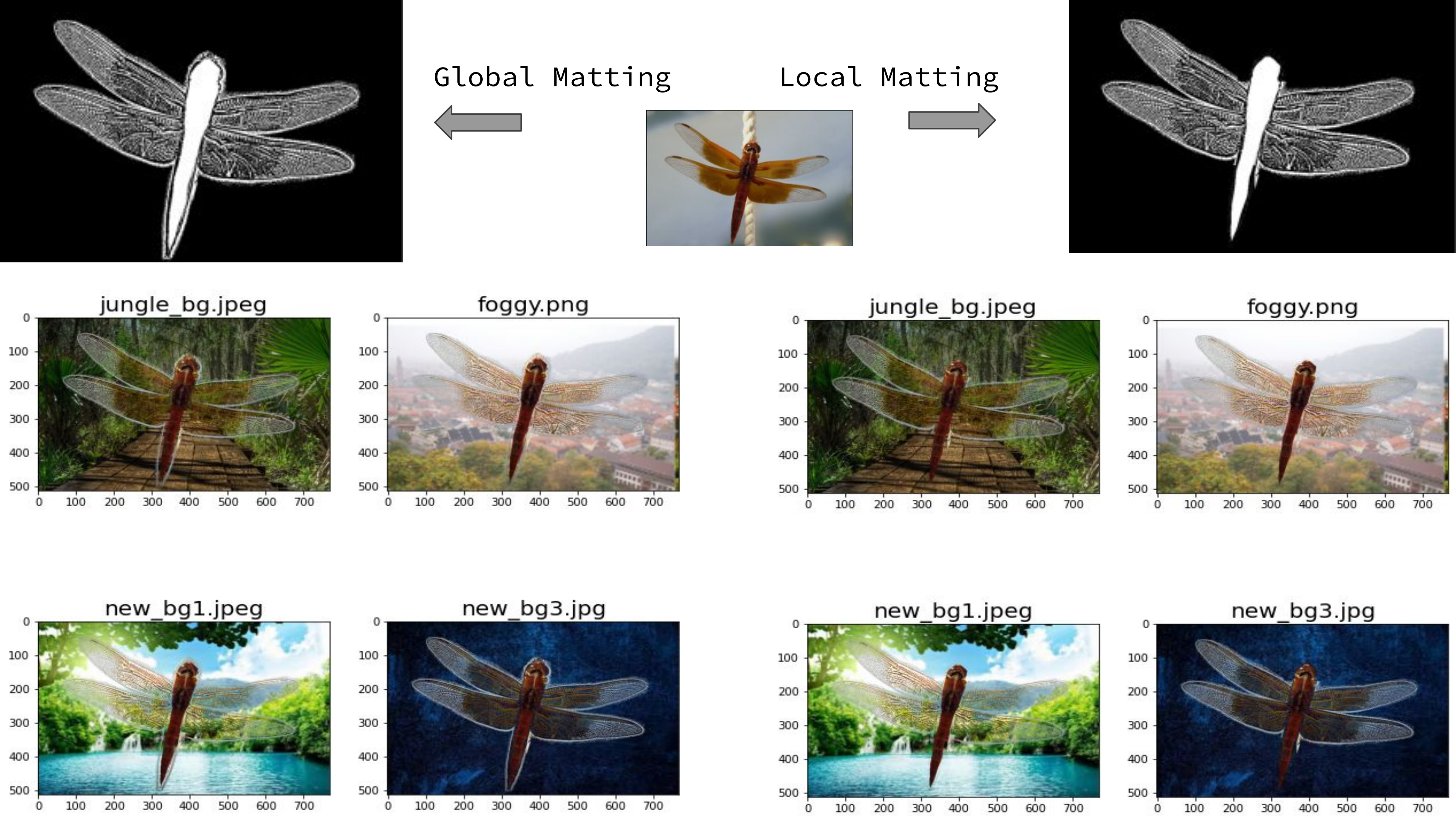
- Above equation can be written as $\boxed{\nabla\alpha = A(\nabla I - D)}$
- This solves to the following.

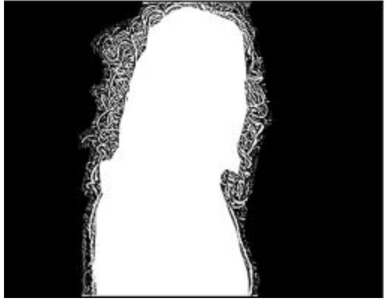
$$\Delta\alpha \approx div(A(\nabla I - D)) \quad \text{s.t.}\ \alpha|_{\partial\Omega} = \begin{cases} 1 & \mathbf{x} \in \Omega_F \\ 0 & \mathbf{x} \in \Omega_B \\ \alpha_g & \mathbf{x} \in \Omega \cap \Omega_L \end{cases}$$

- This can be solved using similar to that of global matting.


Global Matting
Local Matting
jungle_bg.jpeg
foggy.png
jungle_bg.jpeg
foggy.png
new_bg1.jpeg
new_bg3.jpg
new_bg1.jpeg
new_bg3.jpg

Global Matting

Local Matting

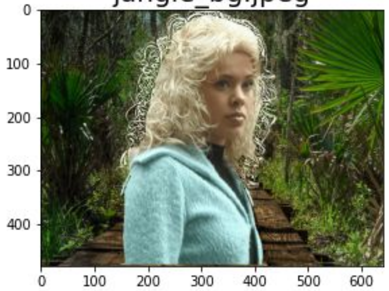
Global Matting

Local Matting

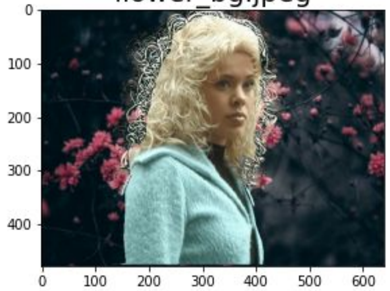
jungle_bg.jpeg


flower_bg.jpeg

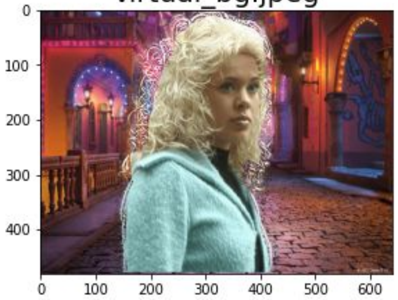

jungle_bg.jpeg



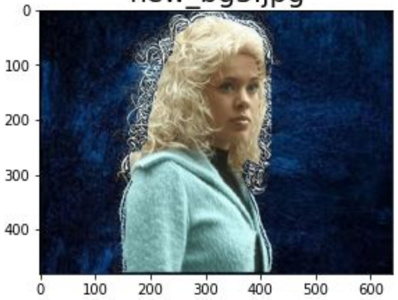

flower_bg.jpeg



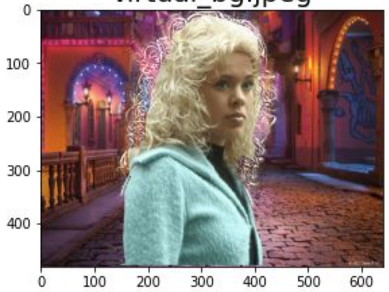

virtual_bg.jpeg



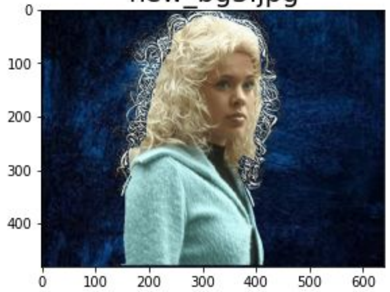

new_bg3.jpg




virtual_bg.jpeg



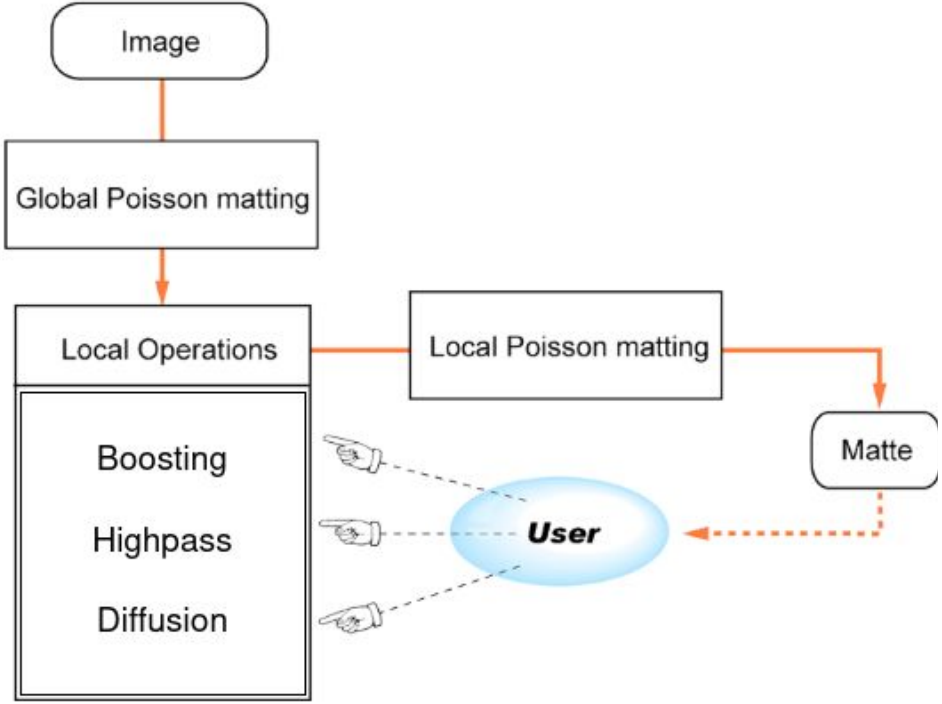

new_bg3.jpg



# Local Operations: Refinement

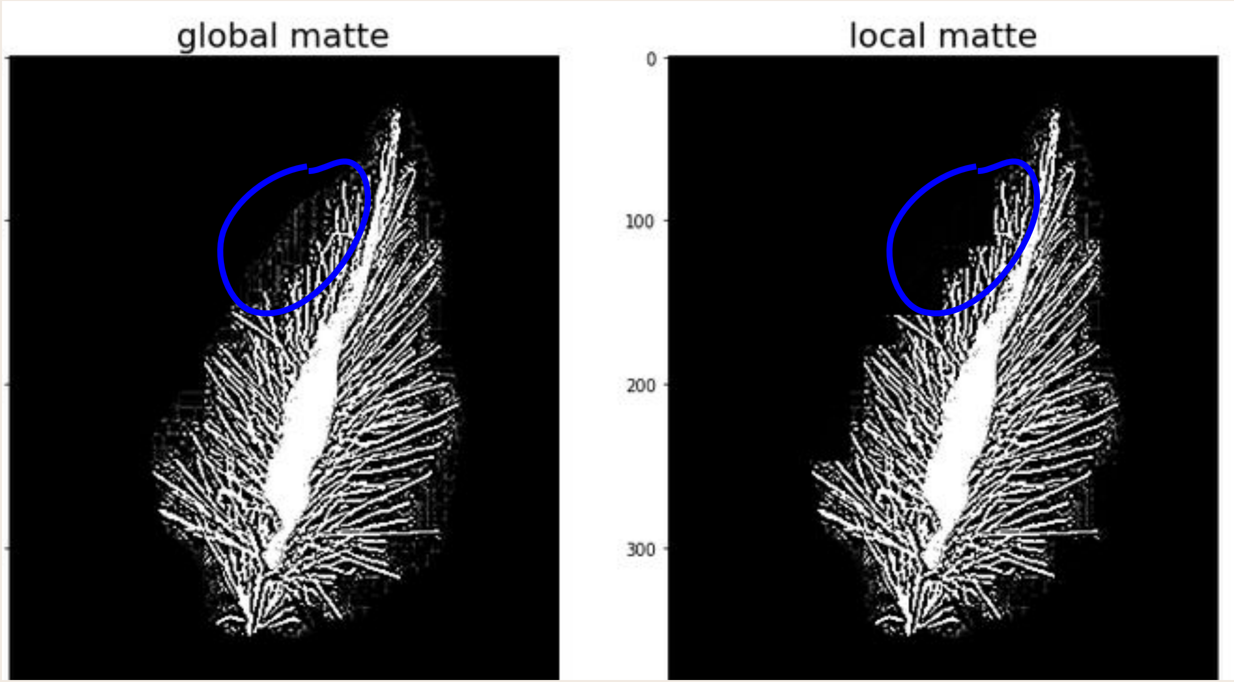
We have implemented the Local Filtering Operations to improve the matte:

- Diffusion (remove noise)
- Highpass (get ~D)
- Boosting (manipulate A)



# Diffusion filtering

Since the image gradient is sensitive to noise, hence anisotropic diffusion is applied on images whenever required[Perona and Malik. 1990] to diffuse image. Then this diffuse image is used for any further local matting.



# High-pass filtering

The channel selection operation generates a smooth background or foreground, leading to low frequency gradients. Therefore, D is be estimated using the low-frequency parts of the image gradient:

$$\mathbf{D} = K * \nabla I$$

where K = N(p; $p_0$ , $\sigma^2$ ) is a Gaussian filter centered at pixel $p_0$ and * is the convolution operator.

The matte is estimates as: **$\nabla\alpha$ =A($\nabla$I - K * $\nabla$I),**

where ($\nabla$I - K * $\nabla$I) corresponds to a high-pass filter.

# Boosting brush

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It smoothes or sharpens the matte by increasing/decreasing A.

It is modifies the Area $A_p$ to $A_p'$ as:

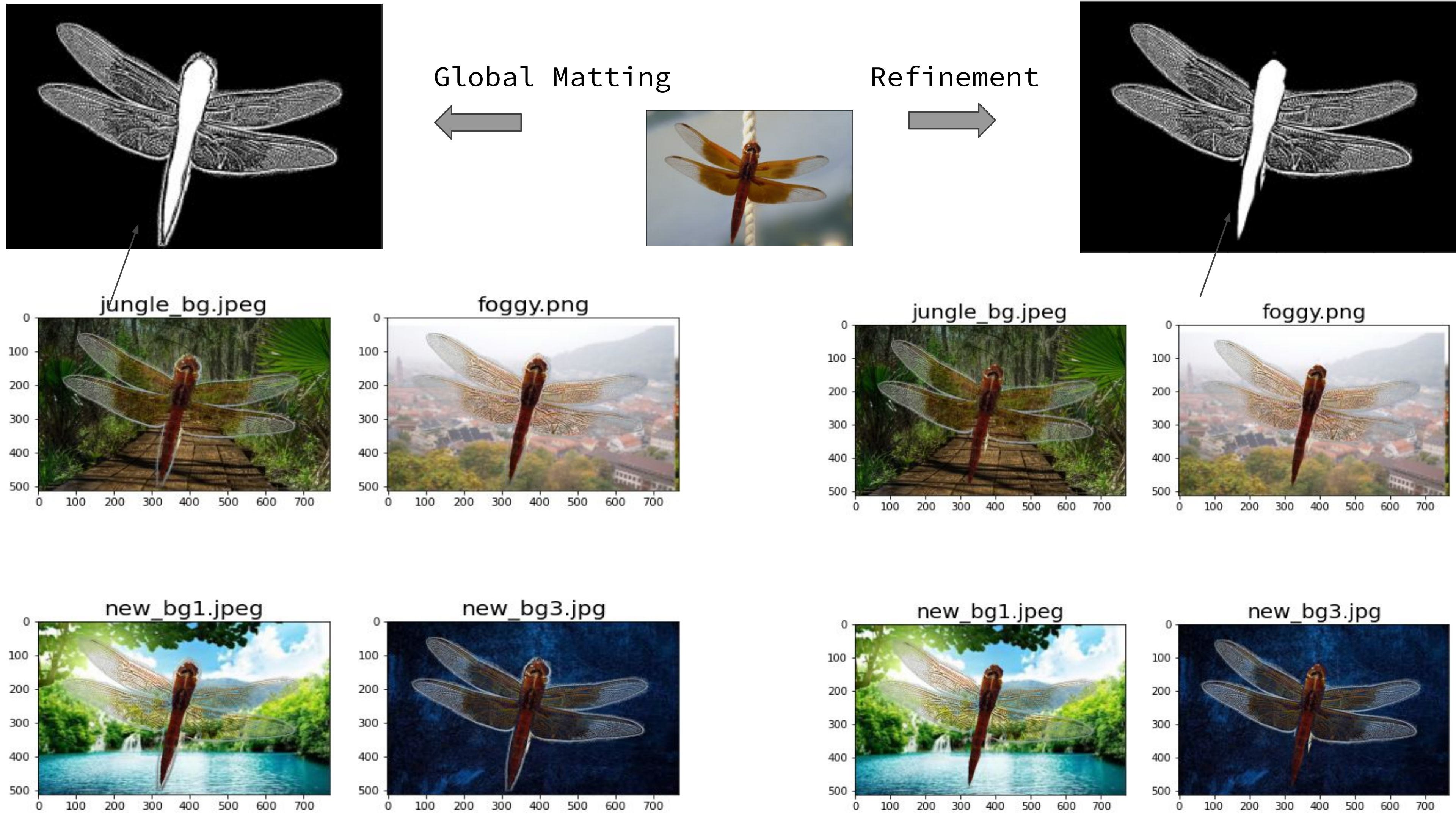
$$A'_p = [1 + \lambda \exp(-\frac{||p - p_0||^2}{2\sigma^2})] \cdot A_p$$

where p0 is the coordinate of the brush center,

σ and λ are user defined parameters which control the size and strength of the boosting.

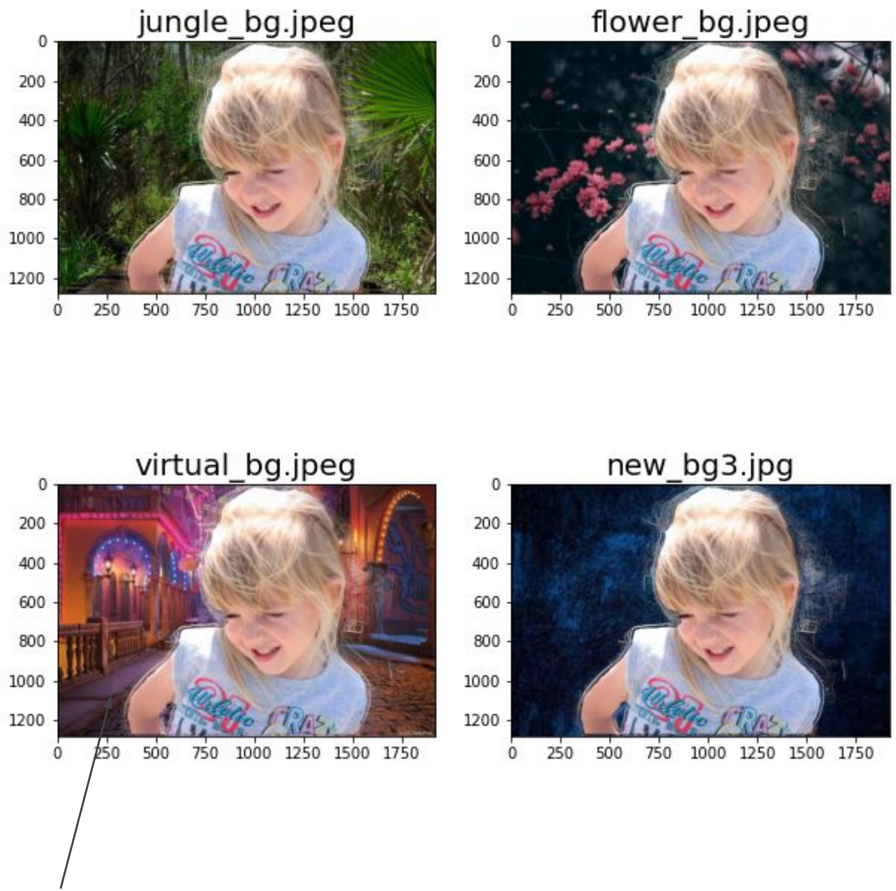
Global Matting
Refinement
jungle_bg.jpeg
flower_bg.jpeg
virtual_bg.jpeg
new_bg3.jpg
jungle_bg.jpeg
flower_bg.jpeg
virtual_bg.jpeg
new_bg3.jpg

Global matting vs Refinement

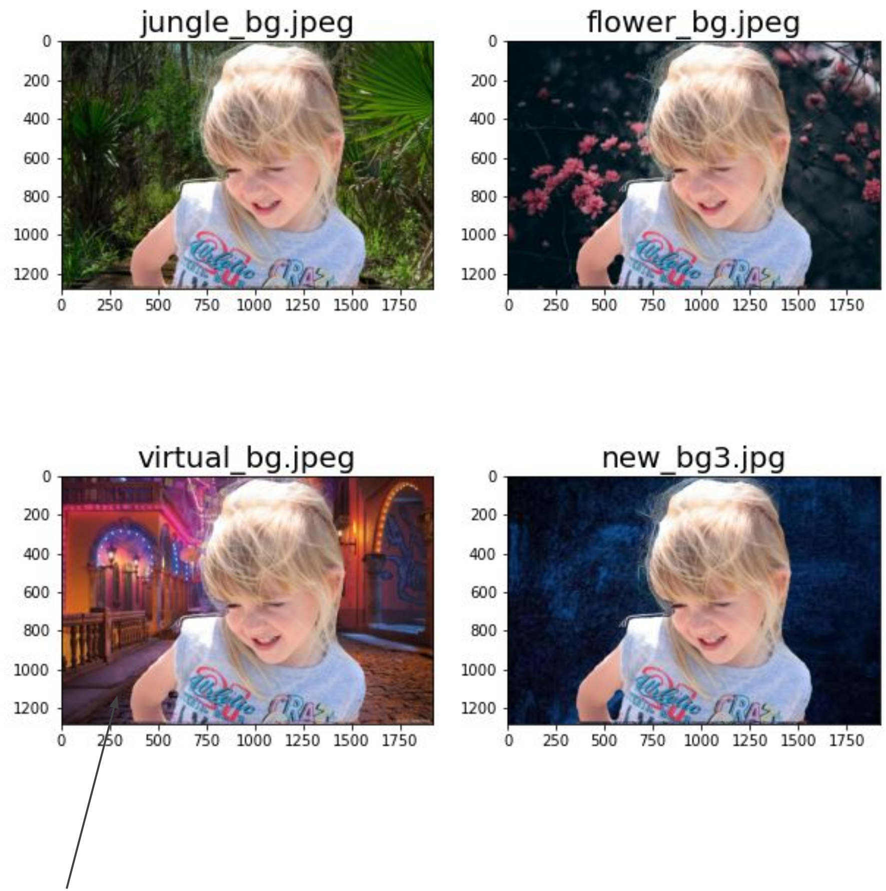


Global Matting
Refinement
jungle_bg.jpeg
foggy.png
new_bg1.jpeg
new_bg3.jpg
jungle_bg.jpeg
foggy.png
new_bg1.jpeg
new_bg3.jpg

global matting results




refined matting results



# Channel Selection

# Channel Selection

For colour images, the poisson equation can differ for each channel. (R/G/B channel)

We try to construct a new channel $\gamma = aR + bG + cB$ with a smooth Background or Foreground.

This way we minimize the variance of the Foreground or Background colors.

# Steps

1) Select the Region of Interest where we wish to apply Channel Selection
2) Compute the weights (a b c) to minimize the sample variances in the new channel. This is solved using the following minimization:

$$\min_{a,b,c} \sum_i [(a\ b\ c) \cdot (R_i\ G_i\ B_i)^T - (a\ b\ c) \cdot (\overline{R}\ \overline{G}\ \overline{B})^T]^2 \quad \text{s.t.} \quad a + b + c = 1$$

where $(\overline{R}\,\overline{G}\,\overline{B})$ are the Mean Intensity in each channel

Note: This implementation was carried out but we were unable to find an appropriate image for the same

# APPLICATIONS

# Multi-Background

When a user has multiple images with **same foreground** but **different background** multi-background method can be used to obtain matte.

- Involves finding:
  - mean image
  - Matte of mean image

Core idea: foreground is same in all images, mean of extracted backgrounds is calculated, Foreground and background are merged to produce **mean-image** which is used to calculate matte.

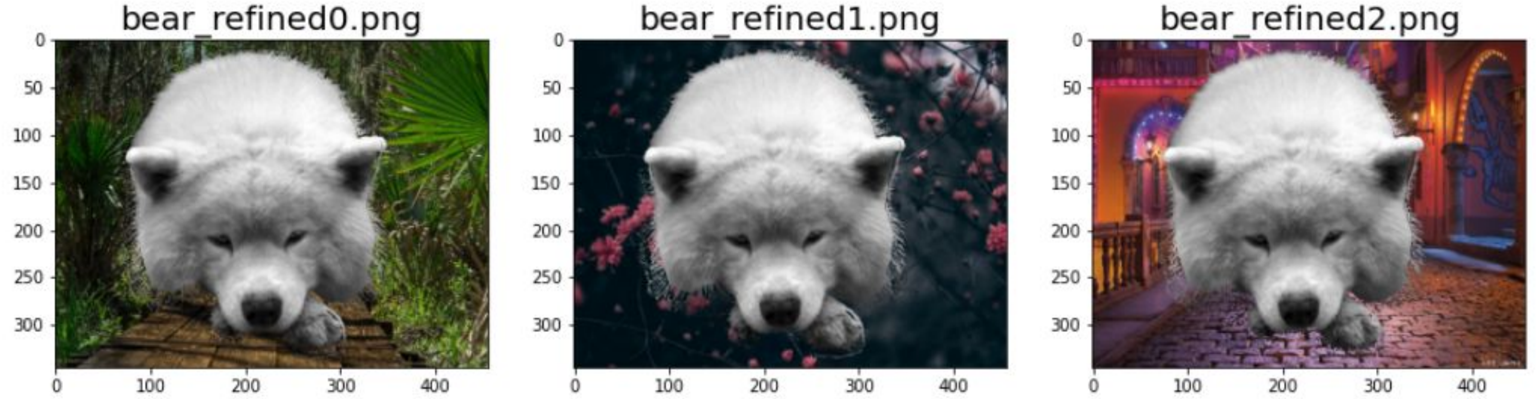
# Multi-Background

Poisson matting when multiple images with same foreground but different background gives better result on mean image which is given

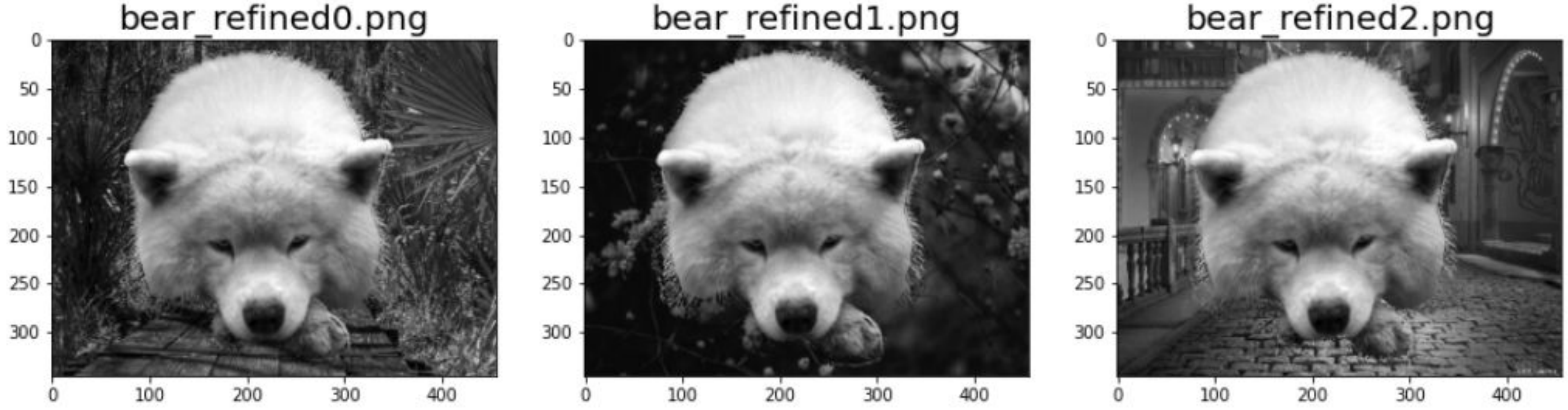
$$\bar{I} = \frac{1}{T}\sum_{t}^{T}(\alpha F + (1-\alpha)B_t) = \alpha F + (1-\alpha)\overline{B}$$

where, T is number of images, alpha is estimated matte of one image, F is estimated foreground, $B_t$: estimated background, $\overline{B}$ is mean bg.

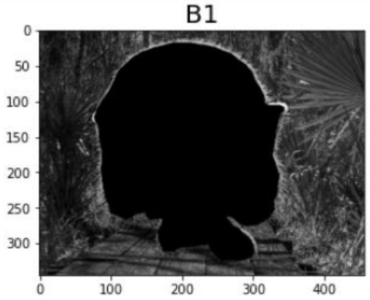
# Mean-bg (input images)

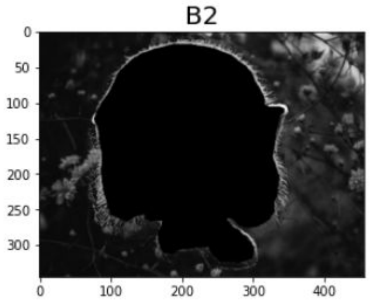


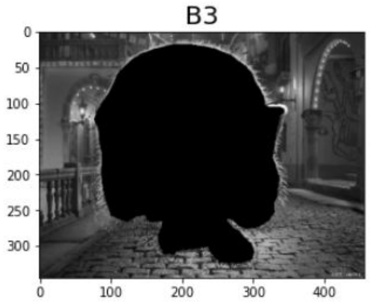

RGB Images

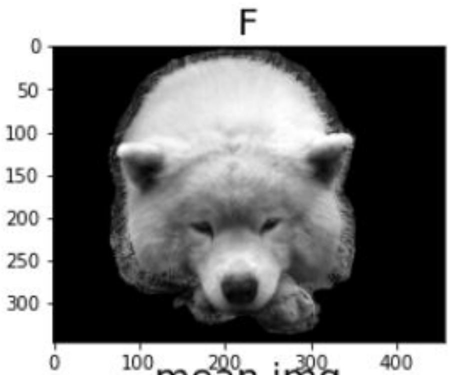


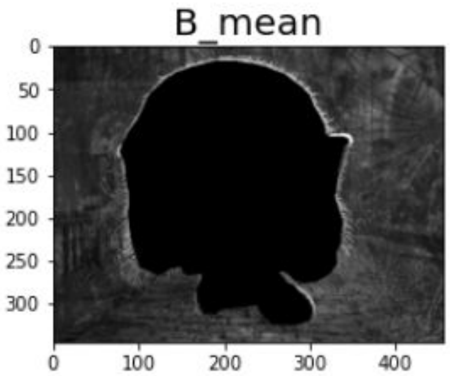

Corresponding Gray-Scale Images

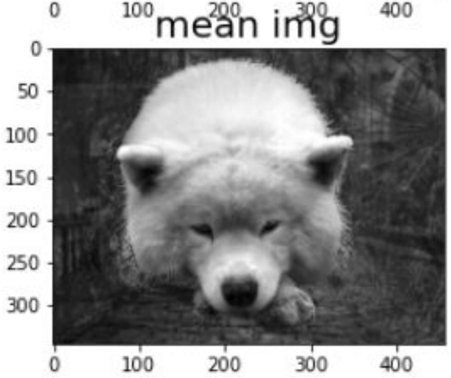


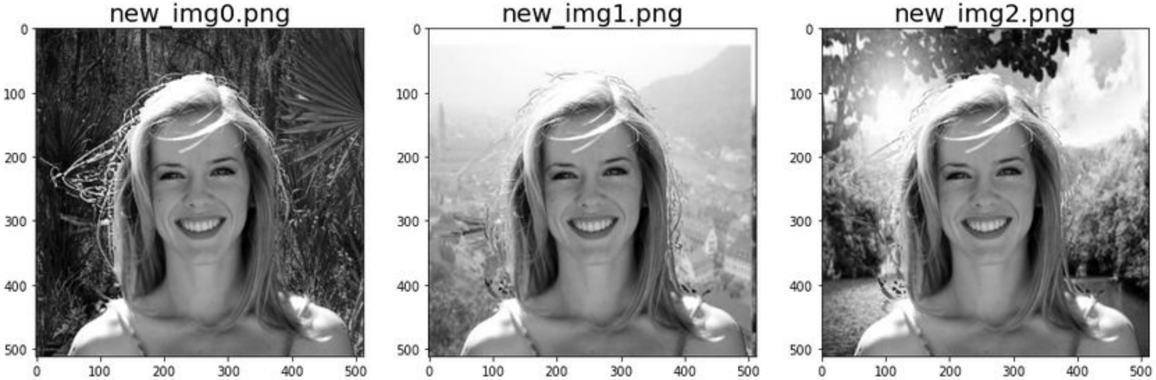



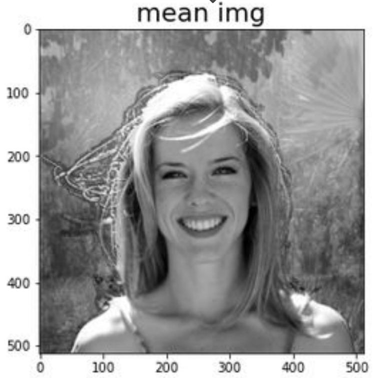



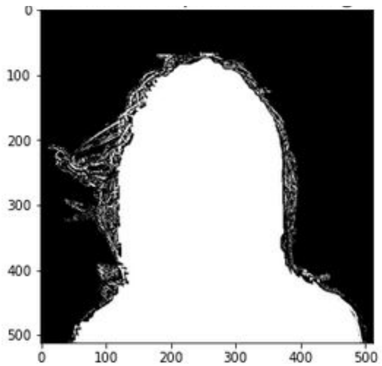

Notice: the **mean image,** is combination of gray-scale input images

Extracted backgrounds




<- Input images



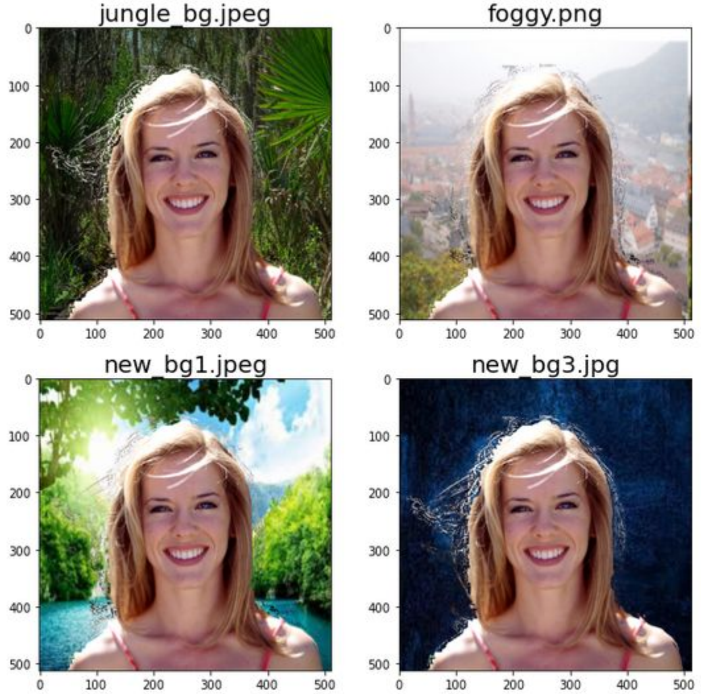



Mean gray image

Matte

Notice: the density and volume of hair reduces

Output images on new bg



# Work Division

| NAME | PARTS ASSIGNED |
|---|---|
| Ansh Puvvada | Global Matting, Fine Tuning of Mattes, Channel Selection |
| Jayati Narang | Local Matting, Diffusion filtering, Fine Tuning of Mattes |
| Avani Gupta | Boosting brush, Refinement of mattes, Multi-Bg, Fine Tuning of Mattes |
| Kajal Sanklecha | Clone brush, Documentation |

# Demo Time!


THANK YOU