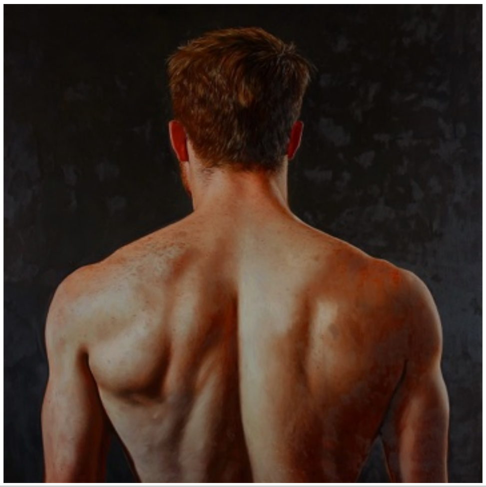
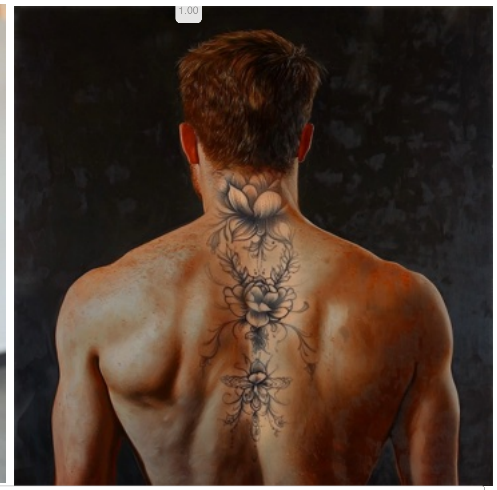
CS180 Project 2 -- Ryan Nader

github: https://github.com/berkeleybear22ryan/CS180_Project2

website: https://berkeleybear22ryan.github.io/CS180_Project2/





SANITY CHECK ------- (PART 0) -- done

This shows the derivative filter is properly catching the edges as I took images with vertical and horizontal lines to see exactly what is happening.

From left to right.

1_imgg.jpeg

2_imgx.jpeg

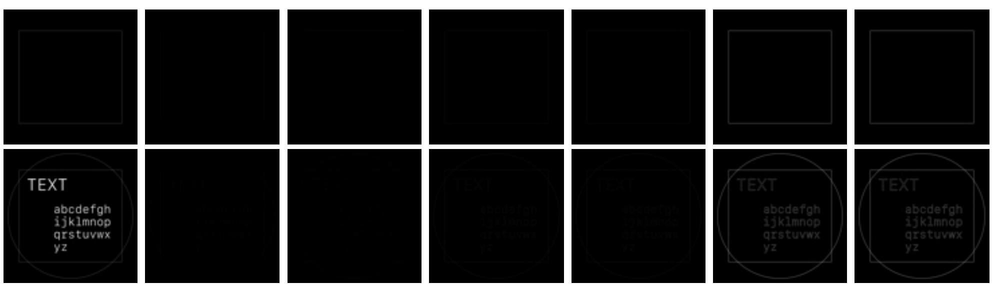
3_imgy.jpeg

4_imgxy.jpeg

5_imgxy_s.jpeg

6_imgxy_bin.jpeg

7_imgxy_s_bin.jpeg




```
 from utility import *

if __name__ == '__main__':
    # TODO: all my images should be between 0 and 255 and are 3d no matter if black and white
    image_number = 12
    image_path = f"./images/{image_number}.jpeg"
    output_path = "./render/part0/"

    image = open_image(image_path)
    print(f"image.shape: {image.shape}")
    print(image.max(), image.min())

    imgg = convolve_v1(image[:, :, 0], G, mode='same', boundary='symm')
    imgx = convolve_v1(imgg, D_x, mode='same', boundary='symm')
    imgy = convolve_v1(imgg, D_y, mode='same', boundary='symm')
    imgxy = combine_images_gradient_magnitude(imgx, imgy)
    imgxy_bin = threshold_image(imgxy, 10)

    # shorter way
    c1 = convolve_v1(G, D_x, mode="full", boundary='fill')
    c2 = convolve_v1(G, D_y, mode="full", boundary='fill')
    imgx_s = convolve_v1(image[:, :, 0], c1, mode='same', boundary='symm')
    imgy_s = convolve_v1(image[:, :, 0], c2, mode='same', boundary='symm')
    imgxy_s = combine_images_gradient_magnitude(imgx_s, imgy_s)
    imgxy_s_bin = threshold_image(imgxy_s, 10)

    save_image(output_path + "1_imgg.jpeg", imgg)
    save_image(output_path + "2_imgx.jpeg", imgx)
    save_image(output_path + "3_imgy.jpeg", imgy)
    save_image(output_path + "4_imgxy.jpeg", imgxy)
    save_image(output_path + "5_imgxy_s.jpeg", imgxy_s)
    save_image(output_path + "6_imgxy_bin.jpeg", imgxy_bin)
    save_image(output_path + "7_imgxy_s_bin.jpeg", imgxy_s_bin)
```

Part 1.1 ------- (PART 1) -- done

1.1 Finite Difference Operator

The code for this is in n1.py.

We will begin by using the finite difference operators as our filters in the x and y directions. These filters are defined as follows: $\mathbf{D_x} = F_1 = \begin{bmatrix} 1 & -1 \end{bmatrix}$ and $\mathbf{D_y} = F_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$.

First, we show the partial derivative in the x and y directions of the image by convolving the image with finite difference operators F_1 and F_2 using the `convolve2d` function from the `scipy.signal` library. Then, we compute the gradient magnitude image. To turn this into an edge image, we binarize the gradient magnitude image by picking an appropriate threshold value, trying to suppress the noise while showing all the real edges.

Original grayscale image used for the processing pipeline.

This image represents the vertical edges detected using the filter F_1 (horizontal difference operator), which calculates the difference between the pixel and its left neighbor.

Convolution operation: $I_x(i, j) = I(i, j) \times 1 + I(i, j-1) \times (-1) = I(i, j) - I(i, j-1)$.

This image represents the horizontal edges detected using the filter F_2 (vertical difference operator), which calculates the difference between the pixel and its upper neighbor.

Convolution operation: $I_y(i, j) = I(i, j) \times 1 + I(i-1, j) \times (-1) = I(i, j) - I(i-1, j)$.

The gradient magnitude combines both horizontal and vertical gradients to represent the overall edge strength at each pixel.

Gradient magnitude calculation: $|\nabla I|(i, j) = \sqrt{I_x^2(i, j) + I_y^2(i, j)}$.

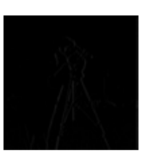
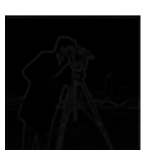
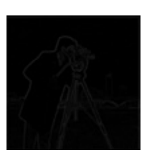
This binary edge map is obtained by applying a threshold (with a value of 75) to the gradient magnitude image. Pixels with gradient magnitude greater than the threshold are considered edges.

Thresholding operation: $I_{I?F?,T=?}(i, j) = \begin{cases} 1 & \text{if } |\nabla I|(i, j) > T \\ 0 & \text{otherwise} \end{cases}$.

Conclusion

In this part, we demonstrated the use of finite difference operators to detect edges in images. By computing the horizontal and vertical derivatives, and then combining them to obtain the gradient magnitude, we successfully identified the edges in the image. The binary edge map highlights the edges by thresholding the gradient magnitude image.

Part 1.2 ------- (PART 2) -- done

Questions

What differences do you see?

The resulting image appears smoother compared to the original.

High-frequency noise will be reduced, making edges more prominent and stable for further processing.

Compared to the results from Part 1.1, the edges detected in the smoothed image should be less noisy and more continuous.

Less noise-induced artifacts are present compared to the unblurred image.

Verify that you get the same result as before. Yes I do!

1.2 Derivative of Gaussian (DoG) Filter

The code for this is in n2.py.

Objective: To reduce the noise in the image and make the edges more distinguishable.

2D Gaussian filter $G(x, y)$ is defined as: $G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$

This is the image with the gaussian filter. The result is a smoothed version of the original grayscale image.

This image (`imgx`) is obtained by convolving the `imgg` image (output from step 1) with the filter `D_x` .

```
imgx = convolve_v1(imgg, D_x, mode='same', boundary='symm')
```

The result represents the gradient of the smoothed image `imgg` in the x-direction. It highlights changes in intensity along the horizontal axis, often used to detect vertical edges.

This image (`imgy`) is obtained by convolving the `imgg` image with the filter `D_y` .

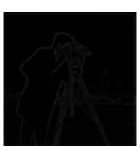
```
imgy = convolve_v1(imgg, D_y, mode='same', boundary='symm')
```

The result represents the gradient of the smoothed image `imgg` in the y-direction. It highlights changes in intensity along the vertical axis, often used to detect horizontal edges.

This image (`imgxy`) is obtained by combining the gradients `imgx` and `imgy` using the function `combine_images_gradient_magnitude` .

```
imgxy = combine_images_gradient_magnitude(imgx, imgy)
```

This is a gradient magnitude image that combines the x and y gradients. It shows the overall strength of the edges regardless of their direction, often visualized as edge intensity.



This image (`imgxy_s`) is obtained by convolving the first channel of the input image with the combined filters `c1` and `c2` (which themselves are convolutions of `G` with `D_x` and `D_y` respectively).

`imgx_s = convolve_v1(image[:, :, 0], c1, mode='same', boundary='symm')` and `imgy_s = convolve_v1(image[:, :, 0], c2, mode='same', boundary='symm')`

```
imgxy_s = combine_images_gradient_magnitude(imgx_s, imgy_s)
```

This image represents a more complex combination of convolutions, which might enhance certain features of the image based on the combined filters `c1` and `c2` . It shows a different gradient magnitude compared to `imgxy` and is the shorter way to get to the image.

This image (`imgxy_bin`) is obtained by applying a threshold to the `imgxy` image.

```
imgxy_bin = threshold_image(imgxy, 10)
```

This is a binary image created from the gradient magnitude `imgxy` using a threshold of 10. Pixels with gradient values greater than 10 are set to 255 (white), and those less than or equal to 10 are set to 0 (black). It highlights strong edges while ignoring weaker ones.

This image (`imgxy_s_bin`) is obtained by applying a threshold to the `imgxy_s` image.

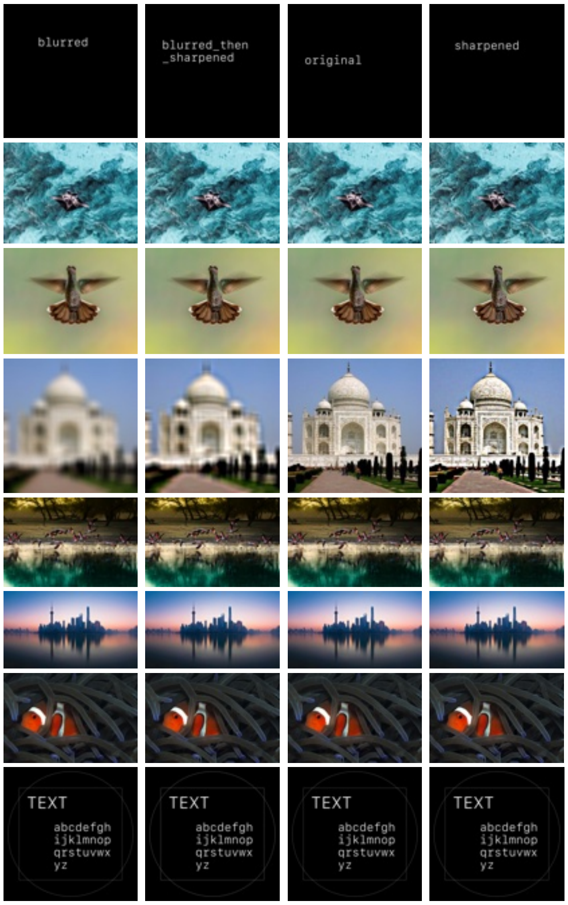
```
imgxy_s_bin = threshold_image(imgxy_s, 10)
```

Similar to `6_imgxy_bin.jpeg`, but applied to the `imgxy_s` image. It represents a binary image created from the `imgxy_s` gradient magnitude image using the same threshold of 10. It highlights strong edges in the `imgxy_s` gradient map.

Part 2.1 ------- (PART 3) -- done

The code for this is in n3.py

The first image is the blurred version created by applying a Gaussian filter, which removes high-frequency details and smooths the image. The second image shows the blurred image after applying unsharp masking, which enhances the sharpness but does not fully restore the original details. The third image is the original unprocessed image, containing all the original sharpness and details. The fourth image is the result of applying unsharp masking directly to the original image, showing enhanced sharpness and emphasized high-frequency details.



Part 2.2 ------- (PART 4) -- done + Little Bells & Whistles (Color)

code for this is in n4.py, also note due to user input requirement for alignment you need to run this on terminal

Note: I tried to make the images all clear based on distance but in general you should open them up in a new tab and move between right up to the screen and 2-8 feet away depends on the image, but they all worked based on my display.

All images are high resolution as well so there should be no issue opening in a new tab.

I also put a lot of time into doing color images and would like the credit for it; however, i found that most of the time the black and white looked better as the blend was more natural and due to the overal less detail it make the images feel more similar and harder for the eye to distinguish.

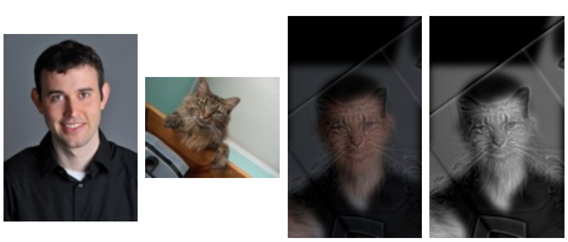
QUESTION: Using color for the low-frequency component typically works better for enhancing the hybrid image effect because it Enhances the perception of the "far" image in the hybrid but in images with lots of different colors blending specific parts that are distinct would probably be even better because the further away colors can ruin the close up view. This also ties in with the idea that color in the high frequency can be distracting and may interfere with the fine details.

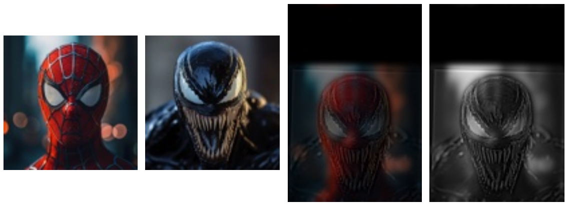
By using color in the low-frequency component, you maintain the natural color perception for the "far" view while allowing the high-frequency details to create the sharp, detailed "near" view without color interference.

all but the text used `sigma1 = 20` , `sigma2 = 10` , and `blend_ratio = 0.5`

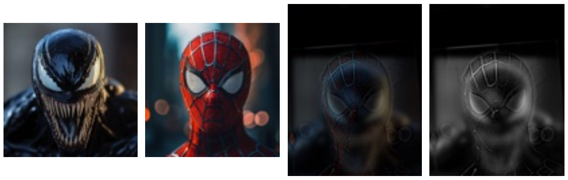
text used `sigma1 = 10` , `sigma2 = 3` , and `blend_ratio = 0.5`

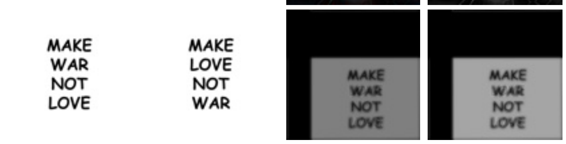
Also note that some of the images could be tuned better, but that would require futher testing, trial and error as well as a stronger method to align them and balance the frequencies, so I decided to leave it.

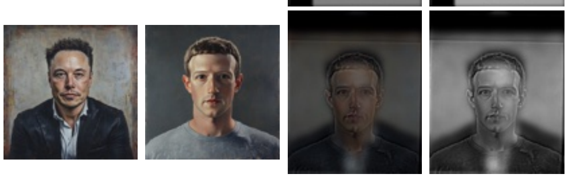


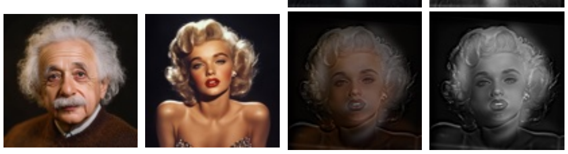


Switched order thought it would be interesting to see, this is my failure one.



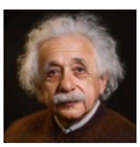


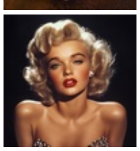




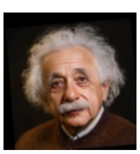
Here is a walkthrough with all the iterations I worked with for a single result.

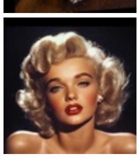
first I started with the following images





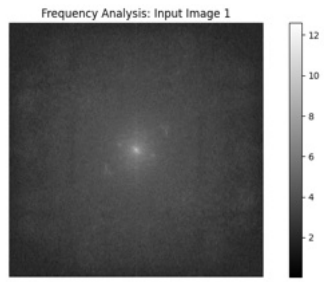
then I make sure to align them using the starter coder and clicking the center of there eyes as that was good reference based on front on shot

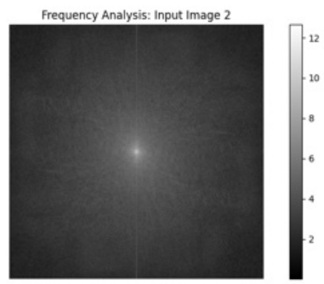


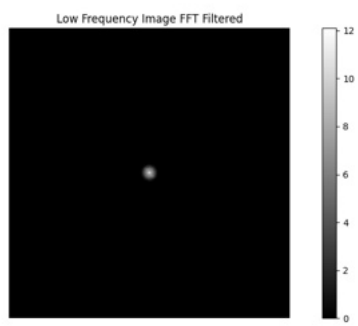


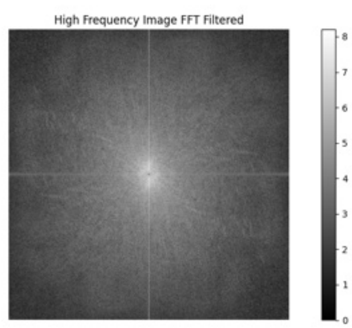
then after it was lined up I rotated it back based on the input image 1

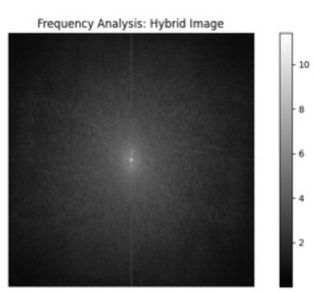
and for this image here is the associated data ... in the order the two input images, the filtered (low then high) images, and the hybrid image

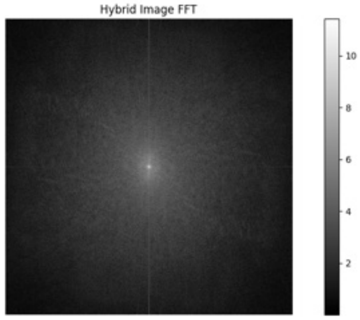




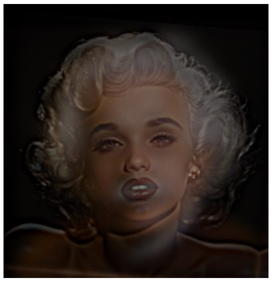


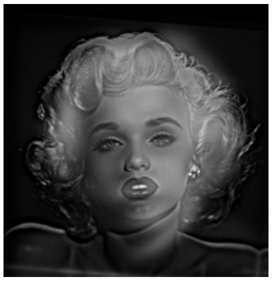






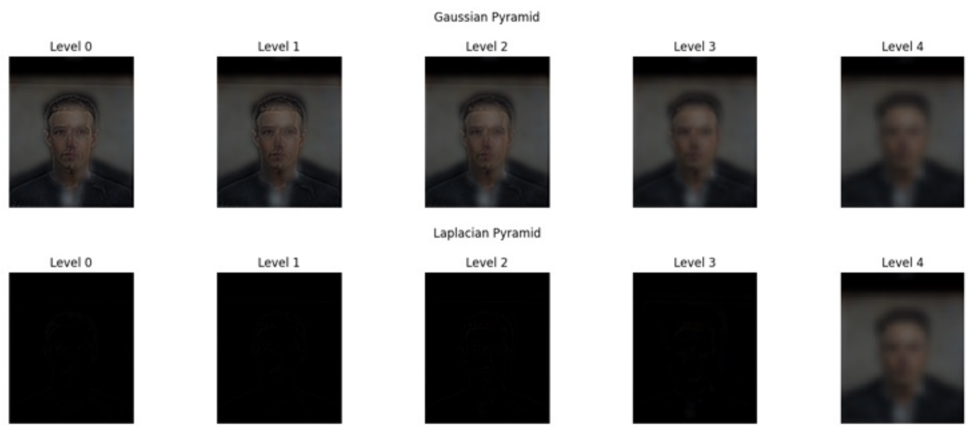
then the final images are ... in black and white and color





these are too high resolution and thus to look proper you have to be far away but ones that look good at this size are ... please stand around 10 feet away to see it work!

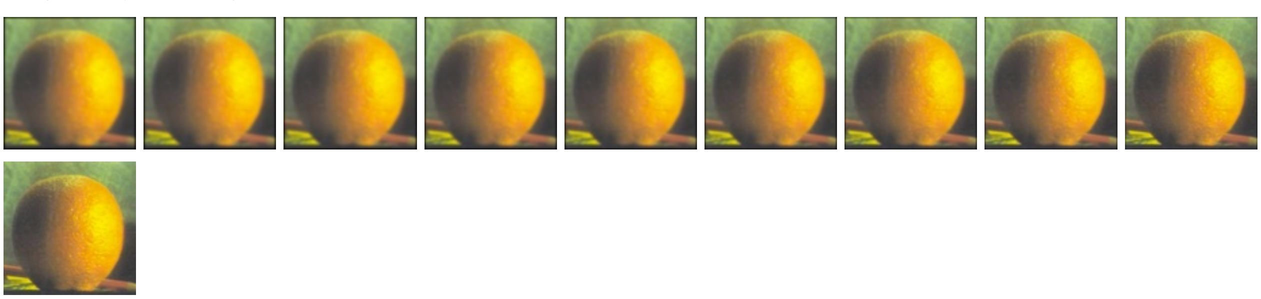
Here is the elon to mark transition ...



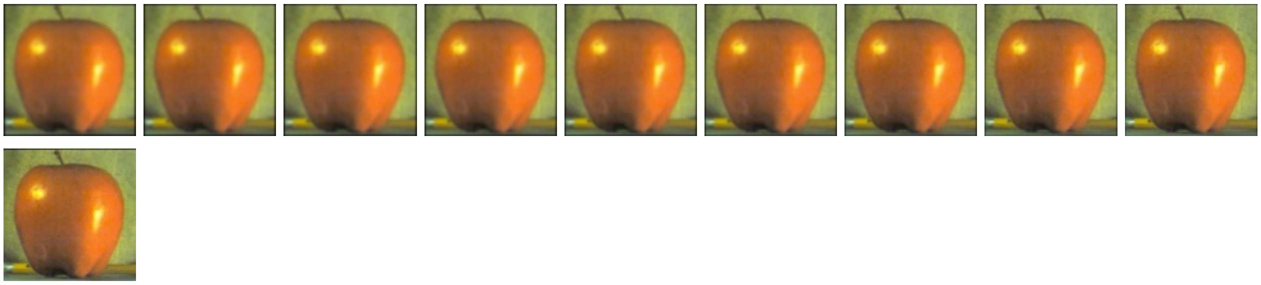
Part 2.3 ------- (PART 5) -- done

The code for this part is in n5.py.

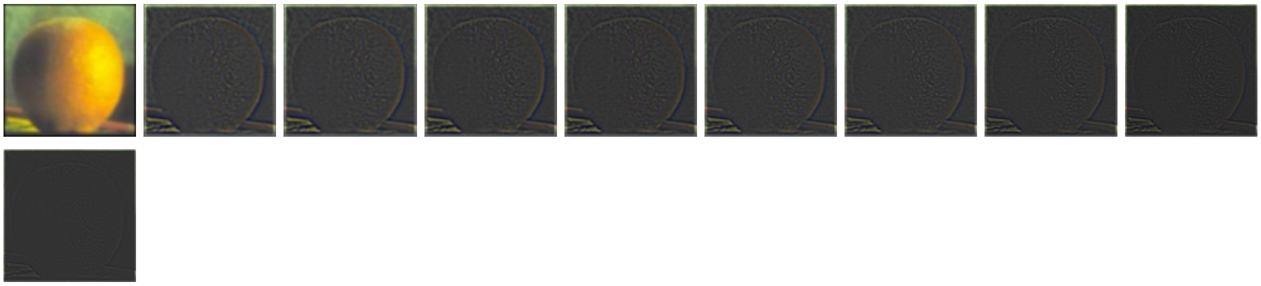
here is the gaussian stack for my level 10 stack for the orange



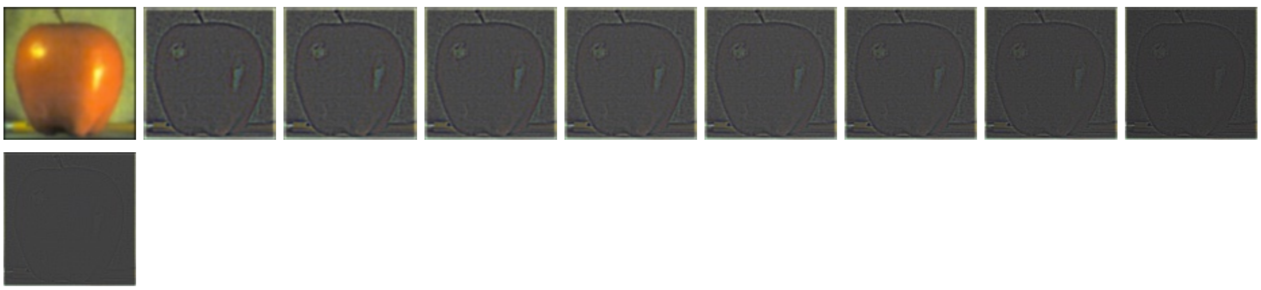
here is the gaussian stack for my level 10 stack for the apple



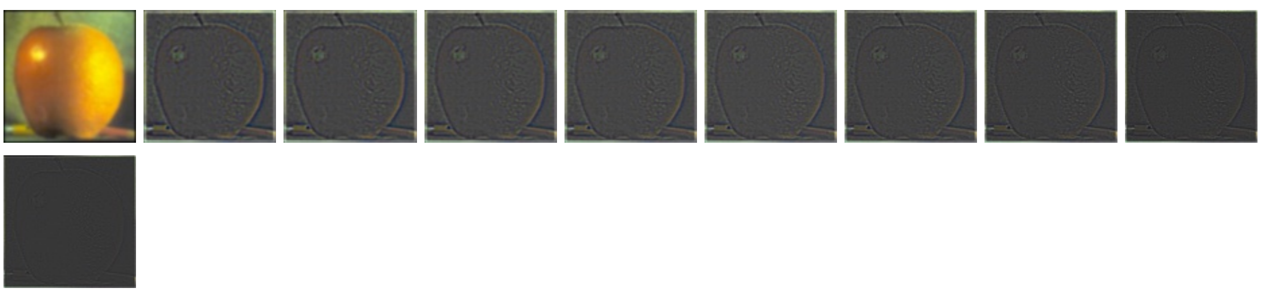
here is the laplacian stack for my level 10 stack for the orange



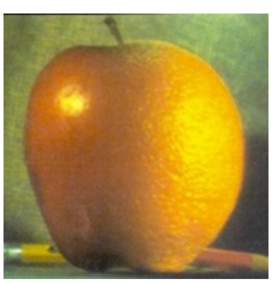
here is the laplacian stack for my level 10 stack for the apple



here is the blended laplacian stack for my level 10 stack for the apple and orange

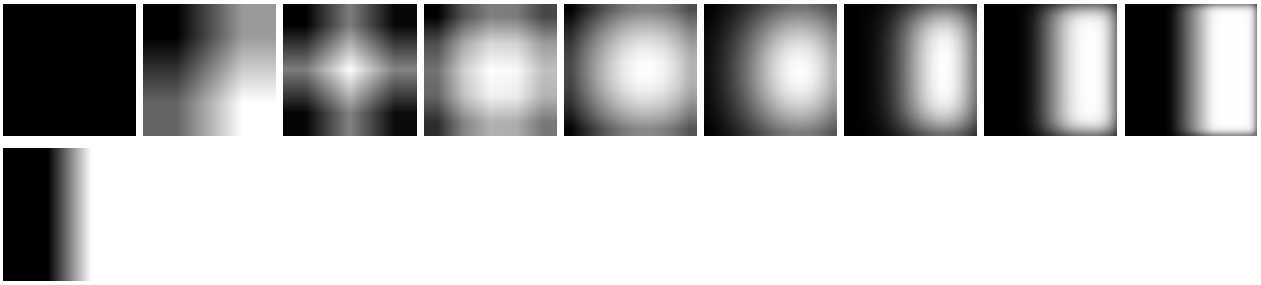


here is the final blended apple and orange

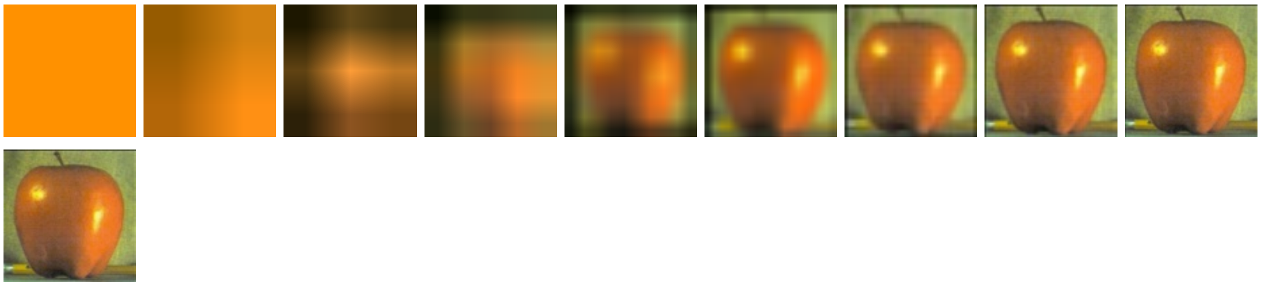


Part 2.4 -------- (PART 5) -- done + Bells & Whistles (Blending)

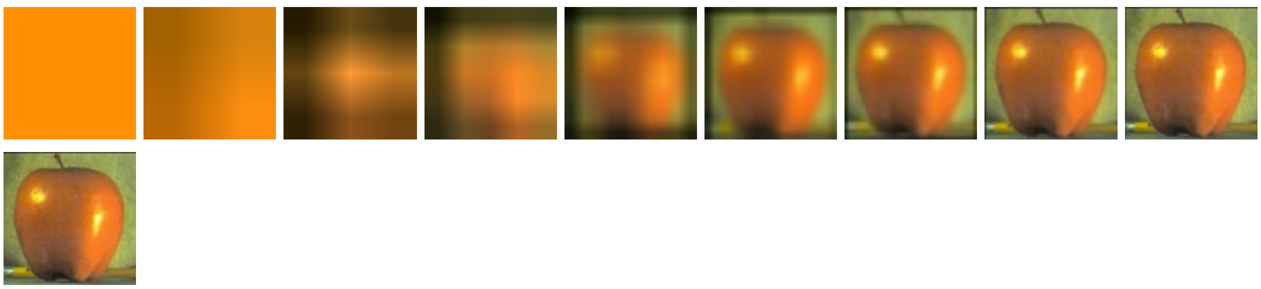
this is the mask with the guassian applied at different resolutions.



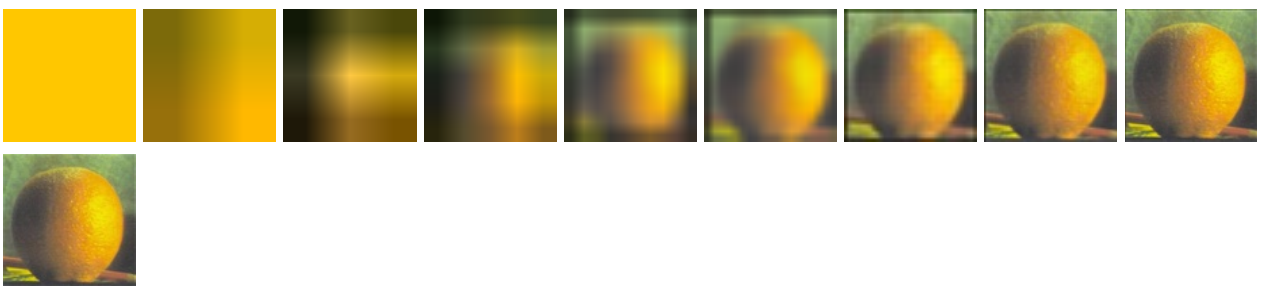
this is the img2 with the laplacian applied at different resolutions.



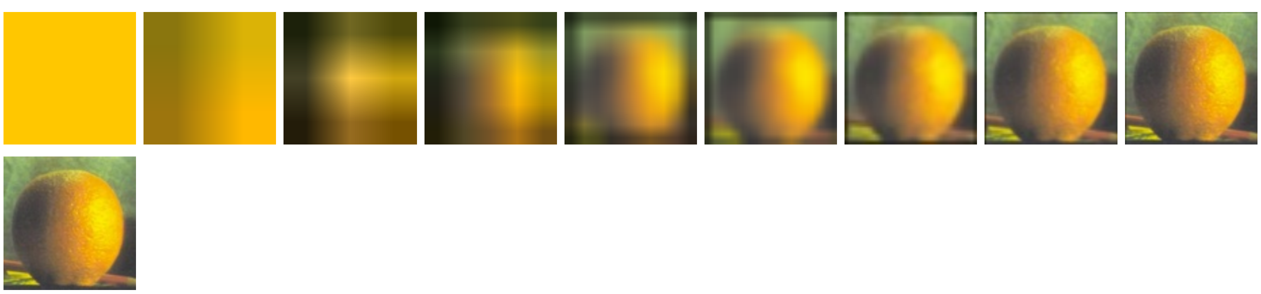
this is the img2 with the gaussian applied at different resolutions.



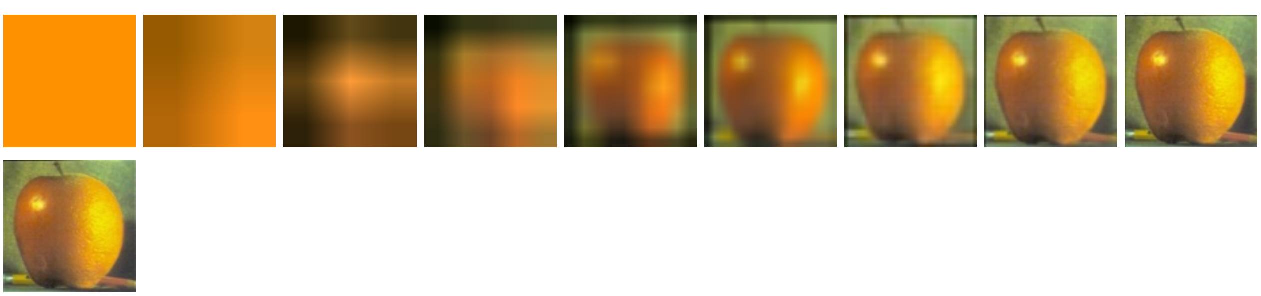
this is the img1 with the laplacian applied at different resolutions.



this is the img1 with the gaussian applied at different resolutions.

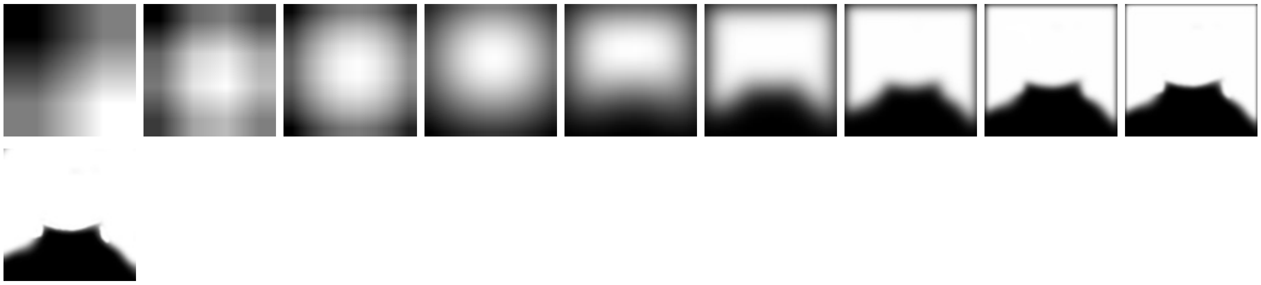


this is the blended img1 and img2 with the laplacian applied at different resolutions.

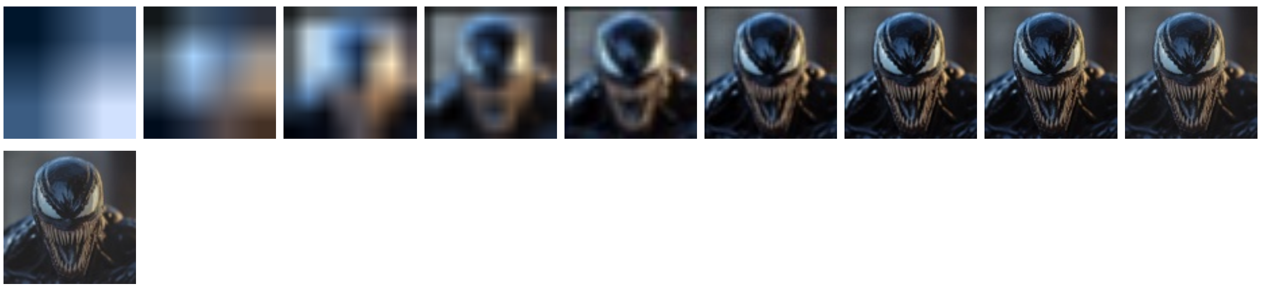


this is the full mask next to the final blended result.

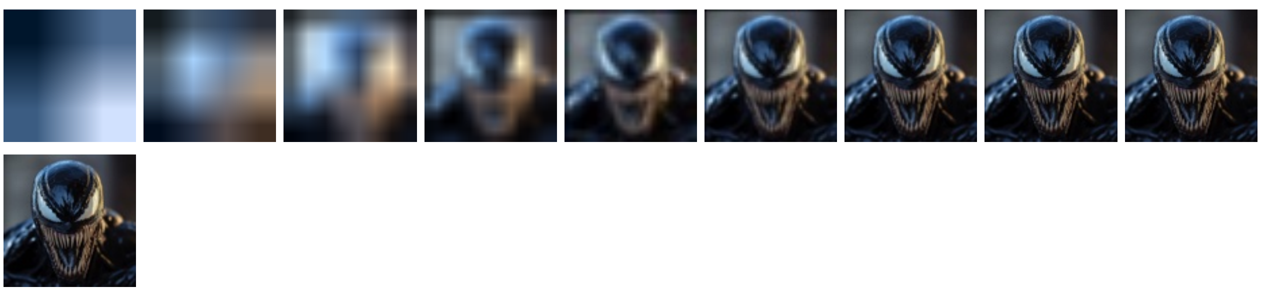
this is the mask with the guassian applied at different resolutions.



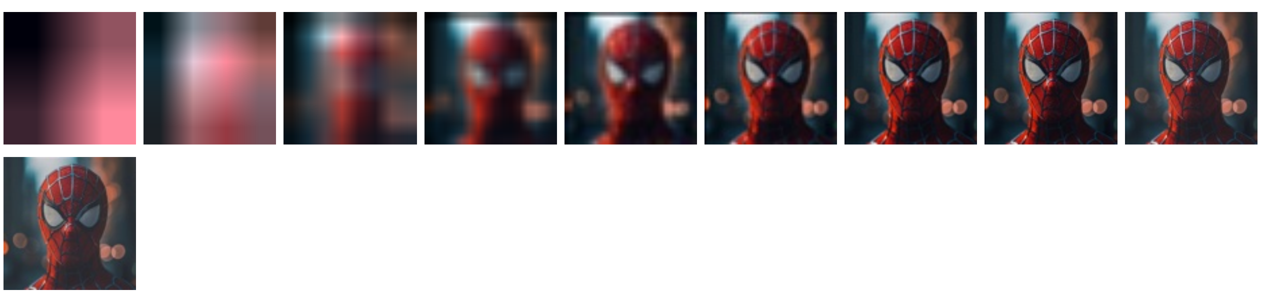
this is the img2 with the laplacian applied at different resolutions.



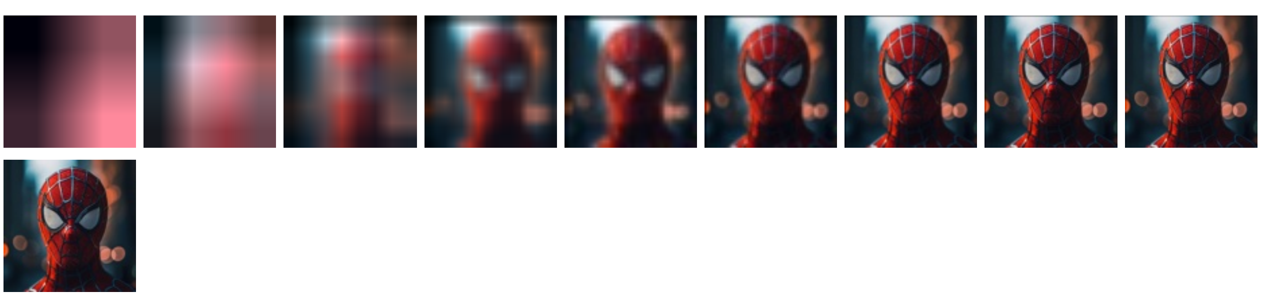
this is the img2 with the gaussian applied at different resolutions.



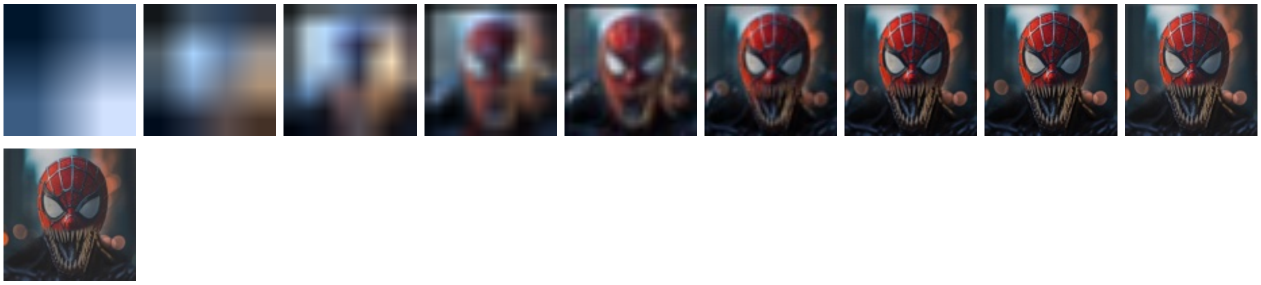
this is the img1 with the laplacian applied at different resolutions.



this is the img1 with the gaussian applied at different resolutions.

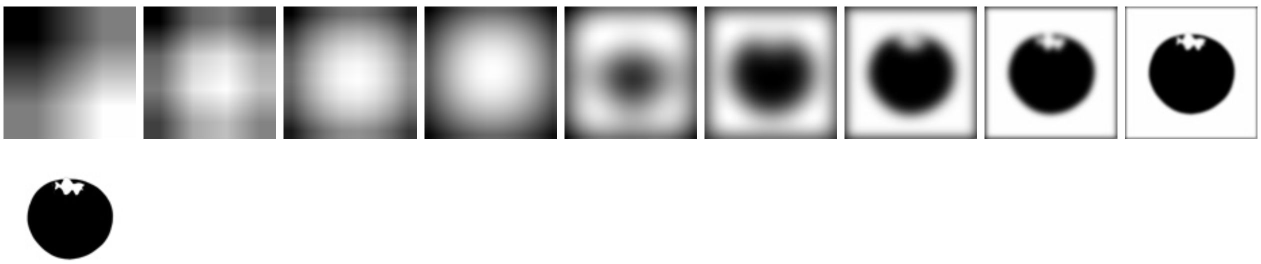


this is the blended img1 and img2 with the laplacian applied at different resolutions.



this is the full mask next to the final blended result.

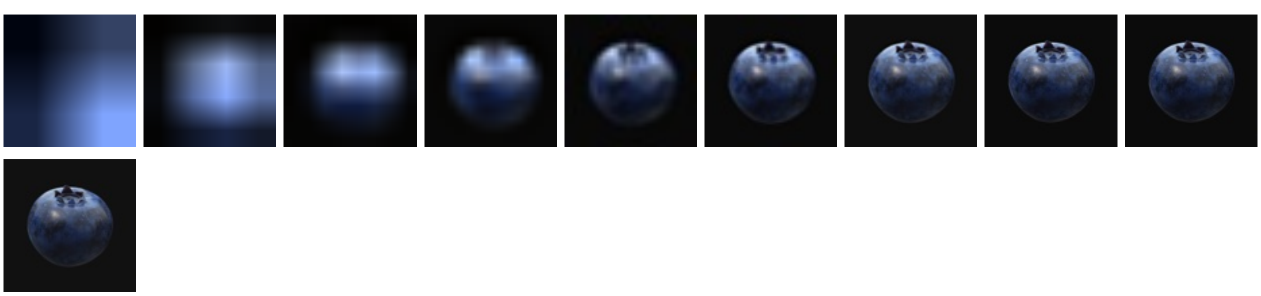
this is the mask with the guassian applied at different resolutions.



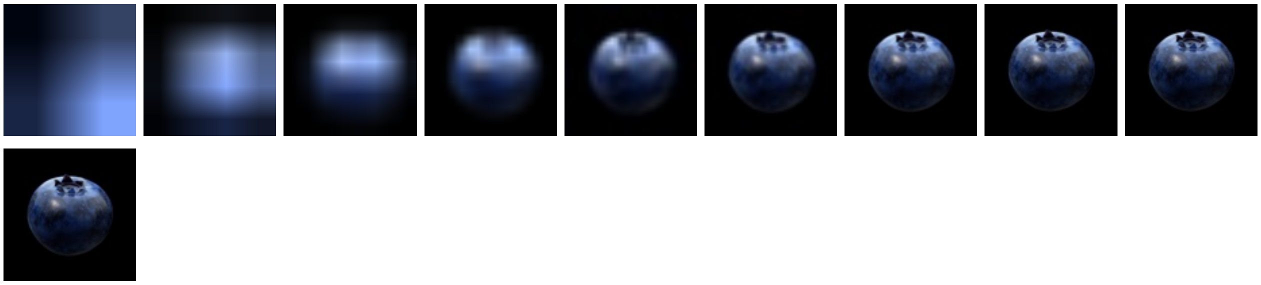
this is the img2 with the laplacian applied at different resolutions.

this is the img2 with the gaussian applied at different resolutions.

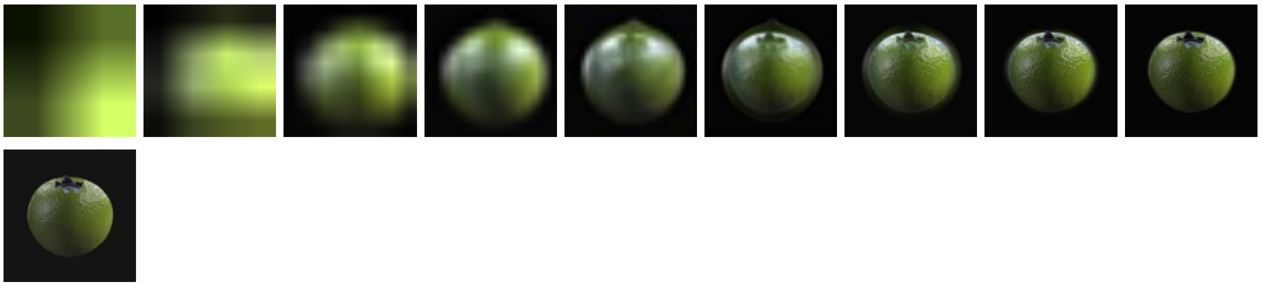
this is the img1 with the laplacian applied at different resolutions.



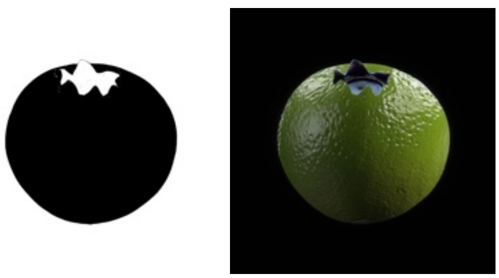
this is the img1 with the gaussian applied at different resolutions.



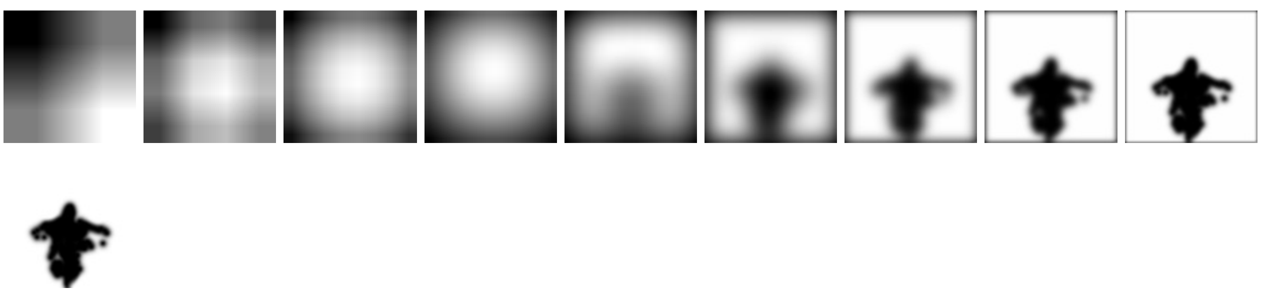
this is the blended img1 and img2 with the laplacian applied at different resolutions.



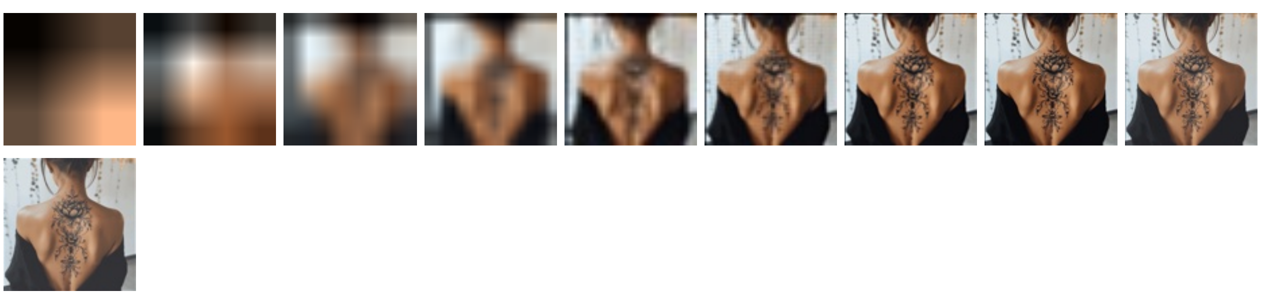
this is the full mask next to the final blended result.



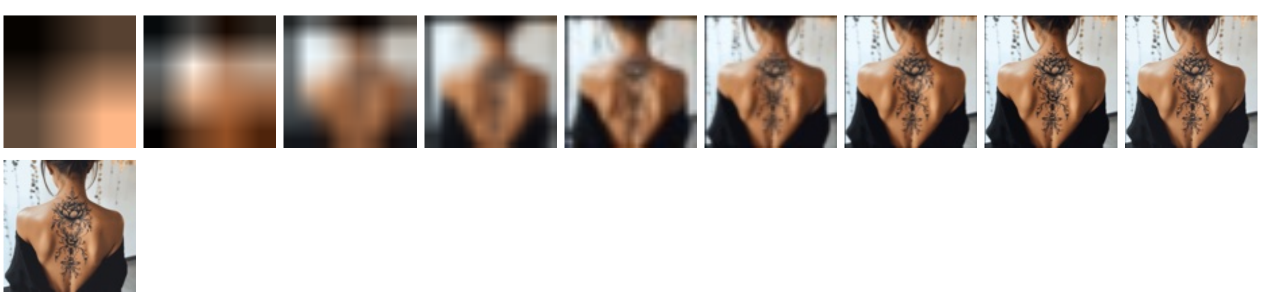
this is the mask with the guassian applied at different resolutions.



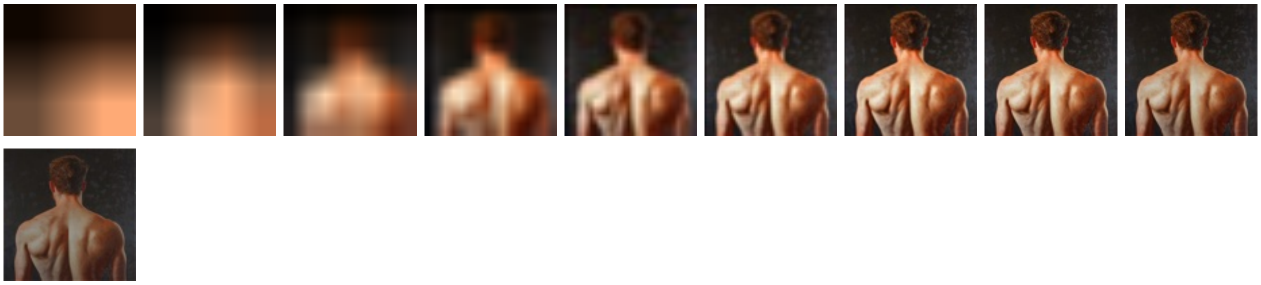
this is the img2 with the laplacian applied at different resolutions.



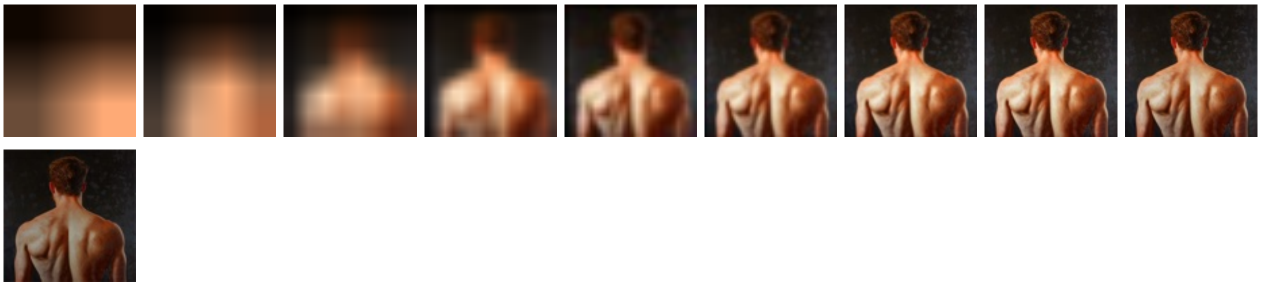
this is the img2 with the gaussian applied at different resolutions.



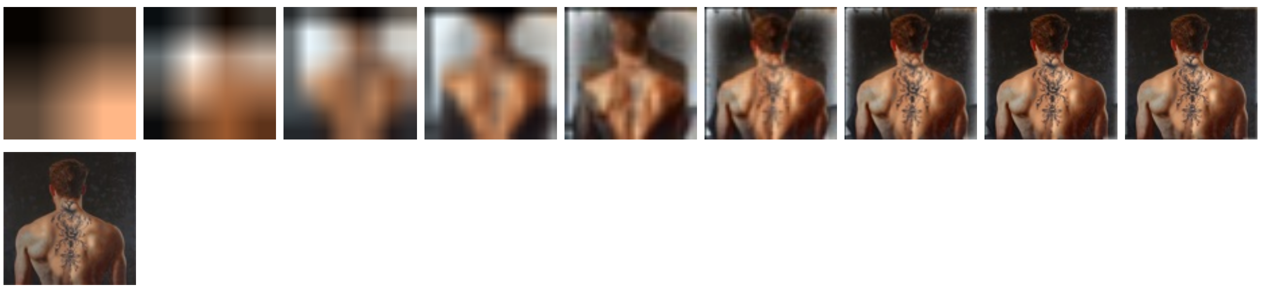
this is the img1 with the laplacian applied at different resolutions.



this is the img1 with the gaussian applied at different resolutions.



this is the blended img1 and img2 with the laplacian applied at different resolutions.

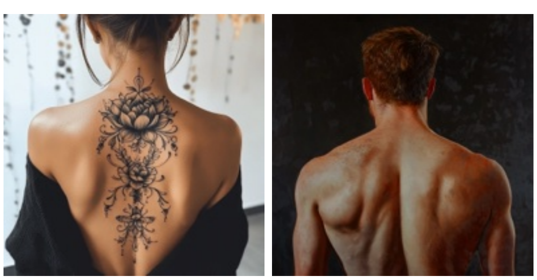


this is the full mask next to the final blended result.

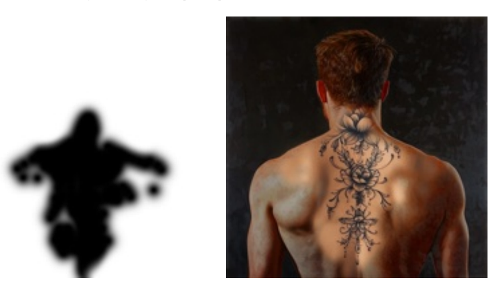
now for extra credit I was able to make it even better than simple filter with the following idea.

I have code function `generate_refined_tattoo_mask` that with tuned line detection was able to map the tattoo area the apply guassian to make it softer. Here are the results.

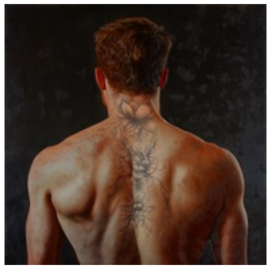
here we have the two original images



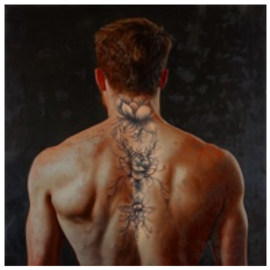
here we have the trivial filter that you could do by hand in photoshop



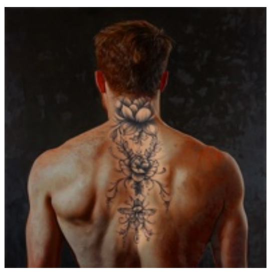
here we have the sobel/canny filter with gaussian at low darkness

here we have the sobel/canny filter with gaussian at medium darkness

here we have the sobel/canny filter with gaussian at high darkness

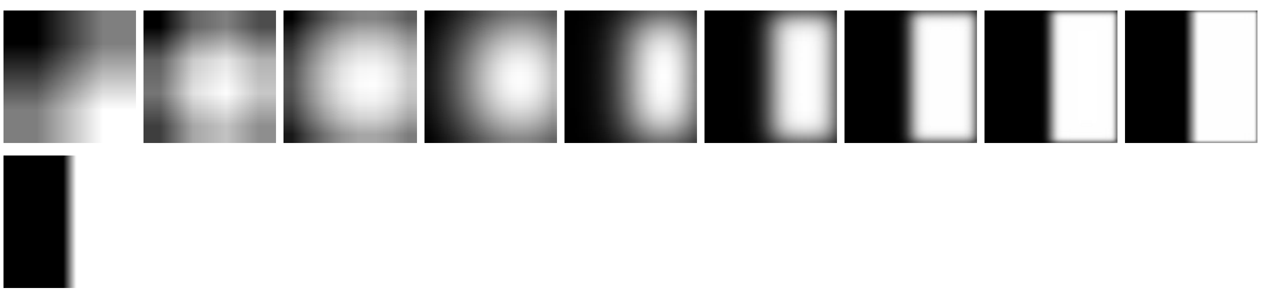



important to note that I also had to clean the filters throughout the process

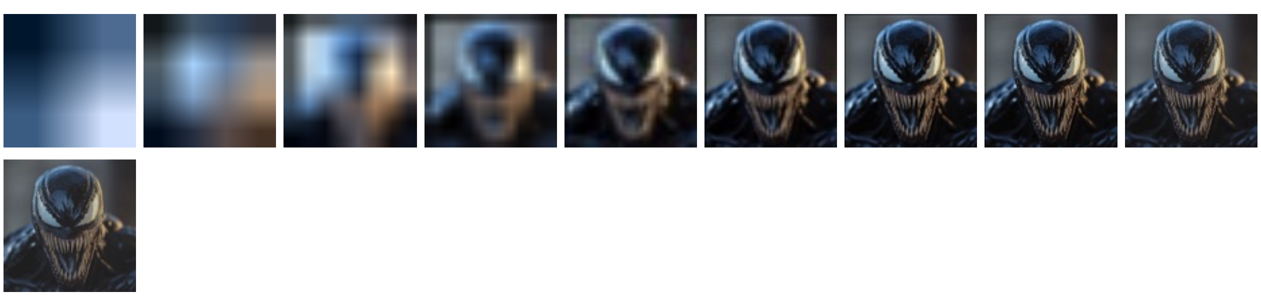

from this you can see that as I make it darker the tattto look better but then he shares issue with the womens skin ton not matching his, so it is a balance game, I like the medium darkness one the best!

Also it is worth noting that I decided not to scale or rotate but this could easily be done so that the entire tattoo fits on his neck and has similiar size.

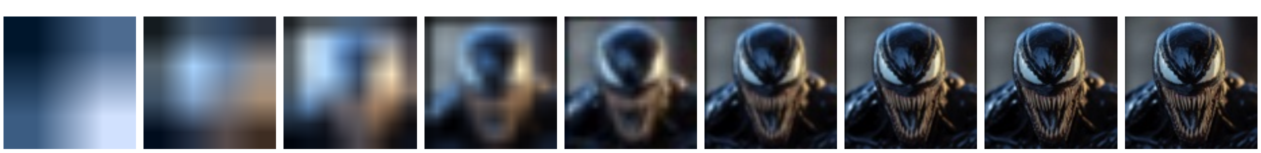
this is the mask with the guassian applied at different resolutions.



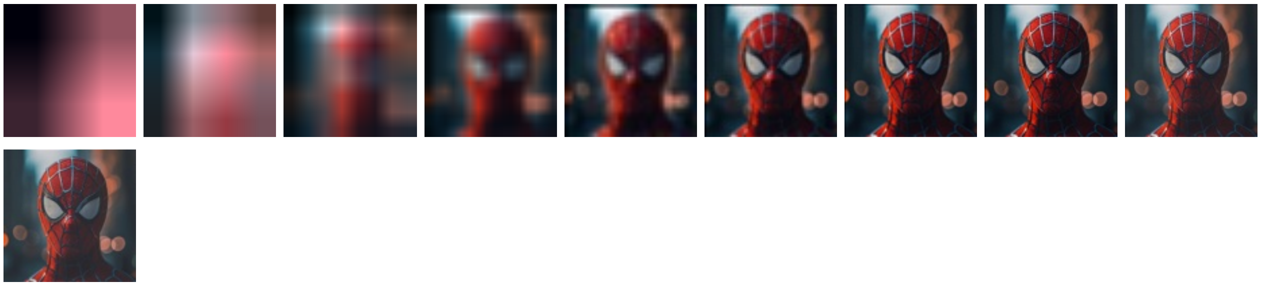
this is the img2 with the laplacian applied at different resolutions.



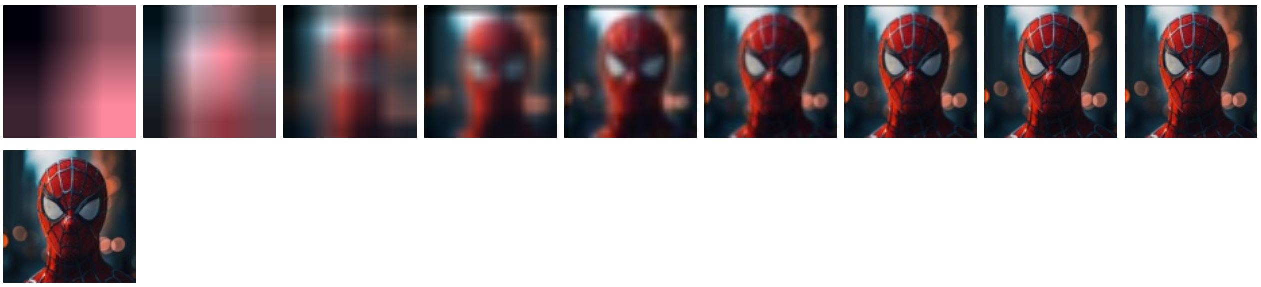
this is the img2 with the gaussian applied at different resolutions.



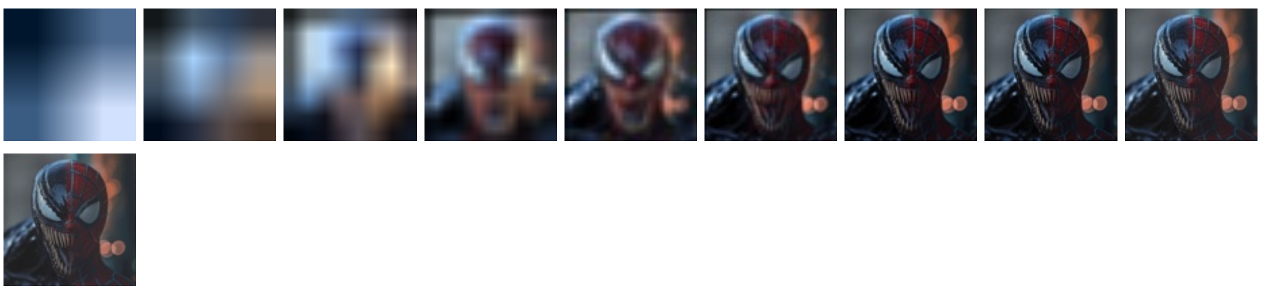
this is the img1 with the laplacian applied at different resolutions.



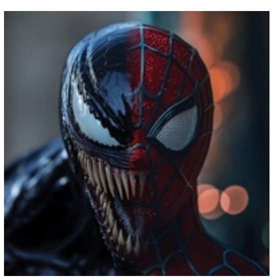
this is the img1 with the gaussian applied at different resolutions.



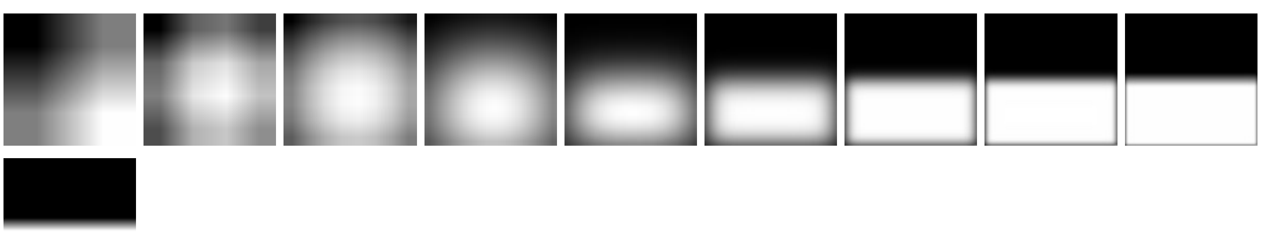
this is the blended img1 and img2 with the laplacian applied at different resolutions.



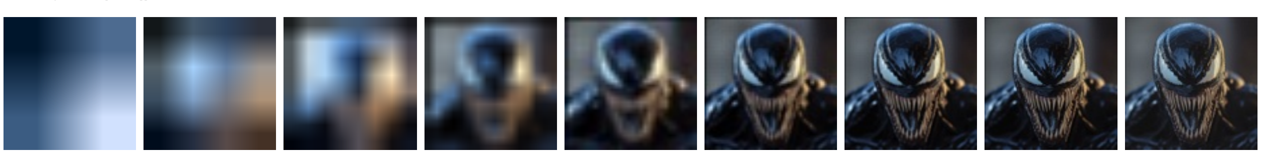
this is the full mask next to the final blended result.



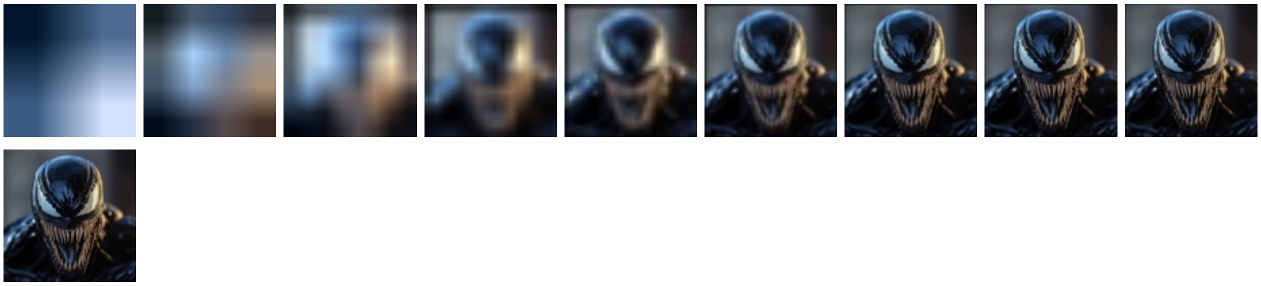
this is the mask with the guassian applied at different resolutions.



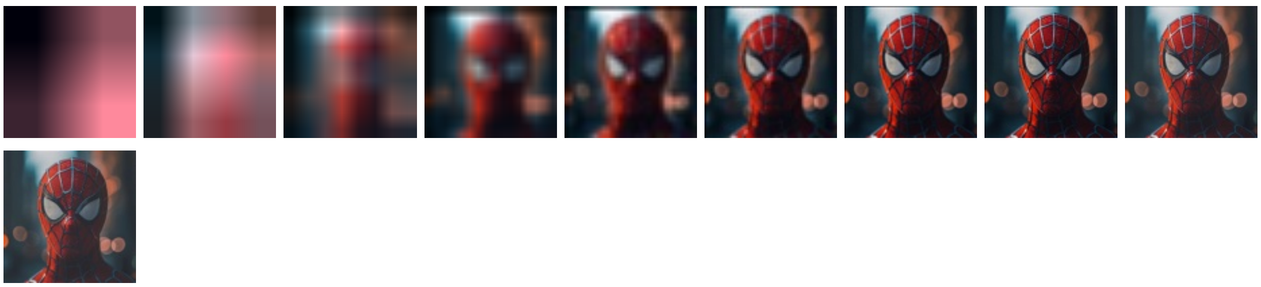
this is the img2 with the laplacian applied at different resolutions.



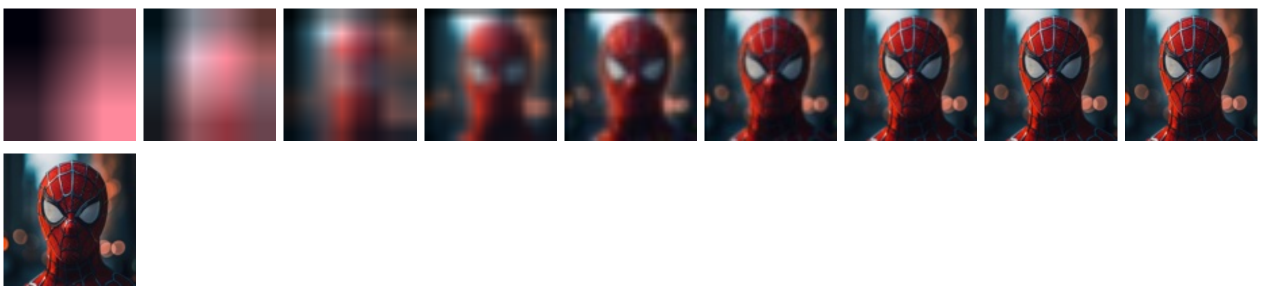
this is the img2 with the gaussian applied at different resolutions.



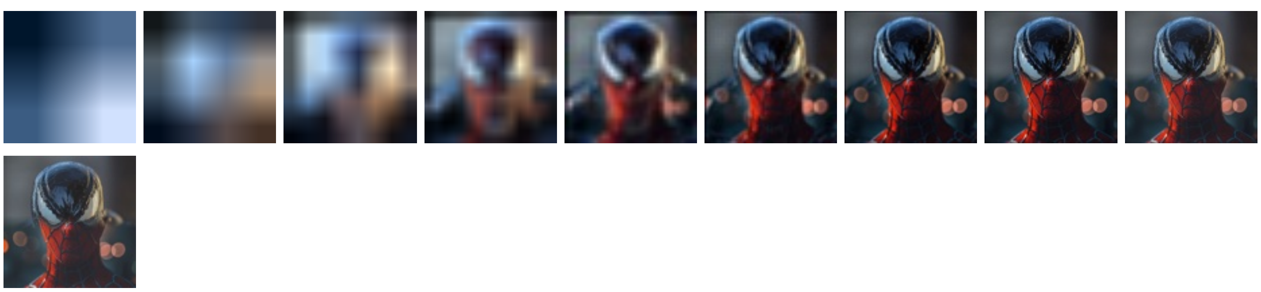
this is the img1 with the laplacian applied at different resolutions.



this is the img1 with the gaussian applied at different resolutions.



this is the blended img1 and img2 with the laplacian applied at different resolutions.



this is the full mask next to the final blended result.