Computer Vision Homework # 1: Image Blending

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Abstract

This report addresses the challenge of seamlessly blending two images. One common approach involves using Gaussian and Laplacian Pyramid to blur both images and then combine them. However, this method often results in a noticeable seam or line in the final image. In this study, I have employed Poisson blending to address this issue and achieve a more seamless and refined result. The code and dataset are available at https://github.com/foreverlasting1202/CV-hw-1/.

1. Introduction

Image blending is a fundamental area that plays a significant role in various computer vision tasks. It involves the seamless integration of multiple images to create a new composite image.

One conventional approach for achieving this is through the use of Laplacian Pyramid (LP). This method, based on the principles of Gaussian smoothing and down-sampling, reduces the mismatches at image boundaries. LP has found widespread application and research, particularly in the field of medical image fusion, such as multimodal medical image fusion [2]. In addition to these techniques, color image fusion has started to gain attention, although research in this field remains relatively limited. But with advancements in sensor technology, color image fusion is expected to receive more attention [4].

While LP methods are often used, they may sometimes result in noticeable seams or lines. To address this issue, there is the concept of abstracting images as functions, leveraging the human eye's sensitivity to second-order derivatives. The idea of Poisson blending (PS) has been developed based on function gradients to improve the quality of the fusion [7].

In this article, I have employed two different methods for image blending and conducted a comparative analysis, identifying the shortcomings of both approaches.

2. Related work

LP. Traditional LP-based image fusion methods have limitations, particularly concerning the preservation of edge information and contrast in the fused images. This has led researchers to propose various improved algorithms. For instance, there is an improved technique known as the "multi-directional Laplacian pyramid image fusion algorithm," which enhances the quality of the fused image by employing multi-directional joint averaging [6]. Several other fusion strategies have also been introduced to enhance traditional LP pyramid algorithms. Examples include a multi-focus image fusion algorithm based on Laplacian pyramids, which retains edge details from the original images while providing stability and noise resistance in the fused image [9]. Another approach combines Laplacian pyramids with discrete wavelet transform (DWT) for image fusion, primarily used in digital image processing to create highly efficient images with minimal distortion [5].

PS. Recently, there have been some notable developments in the field of Poisson image fusion. In particular, Poisson image fusion methods based on Markov Random Field fusion models have been explored. This approach assigns fusion weights, allowing input images to blend in the gradient domain. Subsequently, the fused image is reconstructed from the fusion gradient by solving the Poisson equation using iterative methods. This model has passed standard tests in infrared/visible image fusion and multi-focus/medical image fusion [10]. Furthermore, Poisson image editing techniques have found application in the field of image enhancement. For example, a study introduced a copy-paste image enhancement method for ultrasound images, which uses Poisson image editing techniques to generate realistic and seamless boundary transitions, thereby improving the quality and diversity of training data, providing valuable support for deep learning in advanced image analysis problems [8]. Simultaneously, research has explored Poisson fusion to address some issues in existing infrared and visible image fusion models, such as high complexity, poor real-time performance, excessive input parameters, and the impact of prior knowledge on fusion models [1]. Additionally, an editorial article in 2023 discussed the latest advancements in image fusion and quality improvement, including Poisson image fusion techniques, highlighting the ongoing development in this field and the potential of Poisson image fusion techniques in various image processing applications [3].

3. Method

3.1. Gaussian Pyramid

The main idea of the Gaussian Pyramid is to use Gaussian Blur and subsampling. It downsamples the image multiple times to construct a pyramid-like shape, and the formula is as follows:

$$G_i = \mathrm{PyrDown}(G_{i-1}).$$

Here, $\mathrm{PyrDown}$ represents the downsampling operation, which typically involves convolving the entire image with a 5×5 convolution kernel to apply Gaussian smoothing. Then, even rows and columns are removed from the smoothed image to reduce its size. Stacking these images together results in a pyramid-like structure. G_0 corresponds to the original image.

3.2. Laplacian Pyramid

The Laplacian Pyramid is based on the Gaussian Pyramid and its main concept is derived from the recovery of low-resolution images in the Gaussian Pyramid. An image, after downsampling and then upsampling, cannot be fully restored to its original state. In order to recover the original image with higher resolution during the upsampling process, it is necessary to obtain the information that was lost during sampling. This lost information constitutes the Laplacian Pyramid. Its formula is given by:

$$L_i = G_i - \mathrm{PyrUp}(G_{i+1}).$$

With this approach, we can relatively easily accomplish the task of image restoration to a higher resolution. Here, PyrUp is the inverse operation of $\mathrm{PyrDown}$ and is referred to as upsampling.

3.3. Poisson blending

The main idea behind Poisson blending is to take into account that the human eye is sensitive to second-order derivatives. Therefore, as long as the gradient values within the blending region are specified, and the values at the boundaries of the blend are known, the fused image can be directly determined.

From Figure 2, it can be observed that the first requirement for smoothing is that the values at the boundaries should match the background, which ensures boundary consistency. Since we aim to overlay the reference image, the focus is primarily on the gradients of the reference image. Therefore, it is essential to make the gradients of the

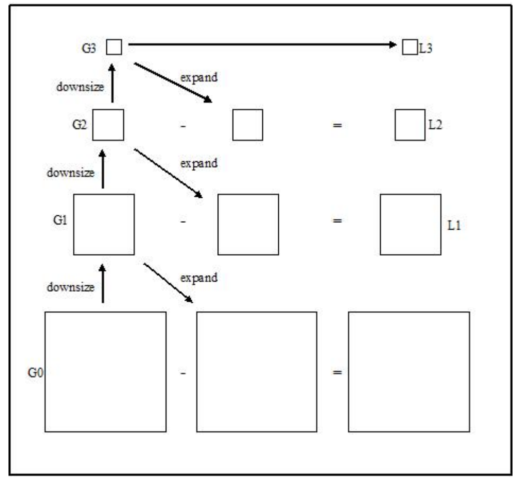

Figure 1. **Gaussian and Laplacian pyramids**

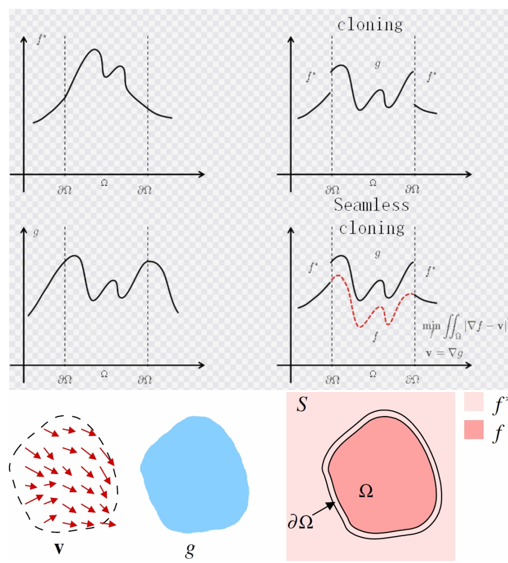

Figure 2. **Poisson Function**

blended content as consistent as possible with those of the reference image.

So, we can obtain the mathematical expression:

$$\min_f \int\int_\Omega |\nabla f - \mathbf{v}|^2, with f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

In order to obtain the minimum of this expression, we need to use the calculus of variations along with the Euler-Lagrange equation, which leads to:

$$\Delta f = \mathrm{div}\mathbf{v}$$

Here, Δ represents the Laplacian operator.

Figure 3. **Dataset**

Figure 4. **Direct Blending**

4. Implementation details

I implement LP and PS with Opencv and Python 3.8 and perform codes on macOS Ventura 13.3.1, M1 pro, 16GB with PyCharm.

5. Experiments

5.1. Datasets, metrics

Datasets. We used four images as a dataset, which include ”ocean” and ”astronomy”, as well as the ”bit” emblem and the ”buaa” emblem. And we will blend the left side of the first image with the right side of the second image.

Metrics. For simplicity, we used visual measurements.

5.2. Experiment Result

Direct.

We can acquire two images after direct blending from Figure 4.

We observed a very poor blending result.

LP.

We can acquire two images after Laplacian Pyramid blending from Figure 5.

It can be observed that the first image has a good result, but there is still a slightly visible separation line in the middle. The second image has an extremely poor result due to unequal border sizes.

Figure 5. **Laplacian Pyramid Blending**

Figure 6. **Poisson Blending**

PS.

We can acquire two images after Poisson blending from Figure 6.

Undoubtedly, the first image is almost perfectly blended, while the second image did not blend well due to the fitting of the Poisson equation.

6. Conclusion

In this paper, we introduced two methods to blend images. At the same time, it can also be observed that the two methods adopt different approaches to image blending. One purely focuses on blending, while the other selects fitting for the final result. This also effectively learned how to implement Laplacian pyramids and Poisson blending using Python and OpenCV.

Limitations.

It can be observed that neither of the two methods is suitable for blending when there is a significant difference between the two images, such as emblem blending. In such cases, using deep learning and GANs (Generative Adversarial Networks) is necessary to achieve better results [11].

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