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Image composition optimization based on feature match and detail preserved

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ABSTRACT

Poisson composition and gradient domain are typical and traditional composition technologies. Their main function is to create a seamless composited image. However, when the original image and the target image have quite a few differences with regard to their features (color, sharpness, noise, texture and so on), the composited image is unrealistic. We use some innovative methods to deal with the problem and there are three main stages considered in the paper. The first stage is to deal with the original image's color ahead of schedule. This is to make the original image as similar as the target image and it contributes to get a realistic composited image. The second stage is to achieve the image's multi-scale composition with wavelet pyramid. The third stage is that we use BLF filter and an image pyramid to preserve the composited image's detail after the image composition. Image composition's optimization is based on the three stages.

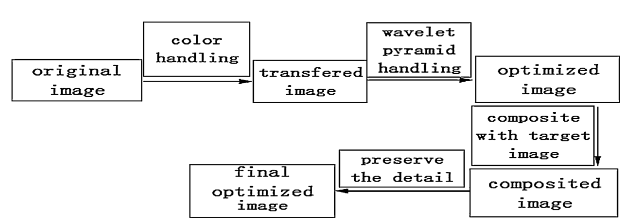
1. Introduction

Image composition's process is about extracting a foreground patch from an original image and pasting it into a new target image. As time went on, the way of gradient-domain filters [1,2] has been used in some papers and some other framework is on the foundation of it. Image matting can transfer extra foreground objects from original image and paste it onto the target image. In conclusion, the prevalent matting approaches [3–5] can get a realistic result. Image cloning can achieve a seamless composited image by using a gradient-domain filter to manipulate pixel values of the image. Edit propagation has been proposed to propagate the local user edits to the rest of the image. Some affinity-based edit propagation methods [6,7] can be effectively used in some works. The classical method K–D Tree [8] is an advanced method on the foundation of other edit propagation methods. However, when the original image's features and the target image's features have apparent differences (color, texture, noise, sharpness, brightness, etc.), the image composition is unrealistic.

Recently, some people lay emphasis on the multi-scale image harmonization [9], as they can harmonize quite a few features between the original image and the target image. On the foundation of it, we use wavelet pyramid to deal with image. The wavelet pyramid is more flexible and we can get a more realistic visual feeling. After the image composition, we use BLF filter and detail layer to preserve the composited image's detail.

2. Framework

In this section, we will introduce our paper's framework. First, we choose the original image and the target image. We use the target image as a reference for handling the original image's color. After our handling, the original image's color will be as similar as the target image. Second, we use an innovative method (wavelet pyramid) to deal with the transferred image. Through ways of histogram matching, noise threshold processing, we can shift the original image's other important features and make them closer to the target image's features. On the foundation of the pretreatment, we can composite the two images. At last, we use the BLF filter and image pyramid to preserve the composited image's detail.



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3. Image composition optimization

In this section, we will give a specific description of the image composition's optimization process. The description contains three parts that are color handling, wavelet handling and detail preserved.

3.1. Color handling

A major problem in the image composition is matching and harmonizing the color between different images. We use an original and parameter-free algorithm to transform any N-dimensional probability density function into another one. After that we can harmonize the two images.

We define the original image as O and define the target image as T. Our destination is to transfer image O's color to match the T. First, we take the condition of one dimension into consideration.

$$u = u + (F(e^T\mathrm{O}) - e^T\mathrm{O})e. \tag{1}$$

In Eq. (1), e is the vector dimension, F is one of the match function and its function is to match different image's color dimension e.

After that, we put our function into practice to higher dimensions $u = [u_0, u_1, \ldots, u_n]$ (if we use RGB component, dimensions u is (R_i, G_i, B_i)). In other words, Eq. (1) extend to higher dimensions.

After we deal with $u = [u_0, u_1, \ldots, u_n]$, we begin to do the remapping. First, we initialize $k = 0$ and the source u. Secondly, we take a rotation matrix $\mathrm{R} = (e_1, e_2, \ldots, e_n)$ and get the color match function from every rotation. Next, we can remap the samples u according to the transformations and the equation is as the following:

$$u^{k+1} = u^k + \mathrm{R}^* \begin{pmatrix} F(e_1^T u^k) - e_1^T u^k \\ F(e_2^T u^k) - e_2^T u^k \\ \vdots \\ F(e_n^T u^k) - e_n^T u^k \end{pmatrix} \tag{2}$$

In Eq. (2), $\mathrm{R} = (e_1, e_2, \ldots, e_n)$. From $k = 0$ to $k = k + 1$ until u match the target the image and every step is much closer to the target.

After the original image's color matching, we continue dealing with the composited image. Our algorithm will change the colors of the background image to harmonize them with the foreground.

3.2. Image's wavelet handling

In the previous pyramid method, we generally achieved the Laplacian pyramid to make texture, noise, and sharpness consistent. In this process, we use a wavelet pyramid image to deal with image. Image's wavelet decomposition is more faster and flexible than Laplacian pyramid. Especially in the domain of noise, texture and sharpness, it has more obvious advantages. Image layers are based on wavelet decomposition. The threshold makes the source and images have similar noise and more other matching features.

First, we decompose the original image and the target with wavelet to achieve a hierarchical multi-resolution image. We define the image's function $f(x, y)$ and its wavelet decomposited equation is as the following:

$$\begin{aligned} f(x,y) &= \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\varphi(j_0, m, n)\varphi_{j,m,n}(x,y) \\ &\quad + \frac{1}{\sqrt{MN}} \sum_{i=H,V,D} \sum_{J=J_0}^{\infty} \sum_m \sum_n W_\psi^i(j, m, n)\psi_{j,m,n}^i(x,y) \\ \varphi_{j,m,n}(x,y) &= 2^{j/2}\varphi(2^j x - m, 2^j y - n), \\ \psi_{j,m,n}^i(x,y) &= 2^{j/2}\psi^i(2^j x - m, 2^j y - n), \quad i = (H, V, D) \end{aligned} \tag{3}$$

After wavelet decomposition, we can get a horizontal and vertical image, one-fourth the size of the original image and H, V, D is its three dimensions.

On the foundation of wavelet decomposition, we achieve color matching, histogram matching, and noise threshold processing for the image's each layer. We can adjust the image's features through making the threshold coefficient. At this point, we can remove discontinuities and remove the excess noise. Then we reconstruct the decomposited image followed by handling the coefficient we need.

3.3. Detail preserved based on BLF filter

After the image composition, we always found that the composited image's detail cannot be preserved as well as before. We use an alternative edge-preserving operator based on the BLF filter which can contribute to decomposite an image to a piecewise smooth base layer and a detail layer.

BLF filter is a nonlinear filter and its main function is to make the image smooth but keep the image's boundary sharp at the same time. Each pixel in the filtered result is a weighted mean of its neighbors, with the weights decreasing both with spatial distance and with difference in value. BLF is calculated on the following basis:

$$\begin{aligned} \mathrm{BLF}(f)_m &= \frac{1}{k_m} \sum_m G_{\sigma_S}(||m - n||) G_{\sigma_r}(||f_m - f_n||) f_n \\ k_m &= \sum_m G_{\sigma_S}(||m - n||) G_{\sigma_r}(f_m - f_n) \end{aligned} \tag{4}$$

In Eq. (4), f is an input image, and the subscripts m and n indicate spatial locations of pixels. Functions G_{σ_r} and G_{σ_r} are classical Gaussians. At the same time, σ_S and σ_r are special coefficients which can determine the filter's result. The σ_S determines the spatial support and σ_r determines the sensitivity to edges. BLF do well with smoothing small changes about intensity and it can preserve the strong edges; however, its ability to achieve coarse progressive is rather limited.

After the introduction of the edge-preserving operator above, we use BLF filter to construct multi-scale edge-preserving decompositions (well-known Laplacian pyramid). The decomposition contains coarse, piecewise smooth and a sequence of difference images.

We define the image g as the original image and construct a $(k + 1)$ as level decomposition. We define $u^1, u^2, \ldots, u^k$ as coarser versions of it and so the k detail layers is represented as:

$$d^i = u^{i-1} - u^i \quad i = 1, \ldots, k \tag{5}$$

In Eq. (5), u^k will serve as the base layer b. When $i = 0$, u^k is the original image.

If we want to get the original image g we can use add the base and the detail layers:

$$g = b + \sum_{i=1}^{k} d^i \tag{6}$$

After BLF filter and decomposition, we can preserve the original image's detail, especially for removing the halo artifacts in the boundary.

4. Experiments and comparison

In this section, we use our innovative methods to do some experiments. At the same time, we compare our experimental results to traditional methods' results.