Interactive Poisson Photometric Propagation for Facial Composite

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Abstract—In image composition, the inconsistent illumination of the source images is one of the major problems for seamless stitching of separated patches. The Poisson image editing is a sound technique for seamless image composition. In this paper, we have generalized and improved this technique and applied it onto solving the illumination discontinuity problem for facial image composition. Toward stitched image with patches of arbitrary shapes, number, and severe photometric discrepancy, an extended Poisson equation is proposed and formulated into a linear equation problem. To solve this equation efficiently, a layer-based Poisson solution propagation algorithm is designed. Based on it, an interactive photometric alignment system for facial compositing image is built. In the experiments, the photometric propagation effects with respect to the standard Poisson editing and other relevant algorithms are compared. Its time performance is also investigated. The experimental results verified the effectiveness and efficiency of the proposed method.

Index Terms—facial composite, Poisson equation, photometric alignment, propagation algorithm, interactive image editing

I. INTRODUCTION

Image composition is the process of cutting patches from different source images and piecing them together seamlessly and naturally. This technique has been widely applied in face image recognition and synthesis studies: facial regions division is a common way to design face image analysis and recognition algorithms [1]; facial composite aims at building computerized system for facial features-based regions division and re-combination [2][3], and it has great potential to be used as an assistant technique for polices to search for criminal suspects [4]; in addition, synthesis of facial expression or aging effects can also be implemented by combining separate regions of eyes, nose, mouth, etc., deriving from sample images of different subjects [5][6].

In facial composite, the difference of illumination effect on each source facial image will inevitably incur discontinuities on the image being stitched. The ordinary solutions toward this problem are some simple image processing operations such as histogram equalization and margin atomization. But they still can not produce satisfactory composition with artifacts totally removed.

Poisson equation is a well known mathematical equation bridging the gradient distribution of a scalar field and the divergence of its vector field. P. Pérez et al. proposed the Poisson image editing technique [7]. The main idea is to construct and solve Poisson equations constrained by the gradient field of source image and the boundary conditions of target image. It has raised much attention and successfully applied in image stitching, panorama synthesis, image completion etc [8-11].

Among these Poisson equation related applications, facial composite is different from other tasks mainly in the following aspects: it has to deal with the multi-patch impacts problem and the arbitrary boundary shape. However, in Poisson editing and image completion, multi-patch can be solved independently, and the straight line boundary in image stitching/panorama makes the Poisson equation easy to be stated. In addition, photos in panorama are usually captured under similar exposure condition. However, facial composite photos may come from totally different camera parameters, resulting in severe photometric discrepancy among them. Color bias problem will inevitably occur in pixels far from the constraint boundary. Human are so sensitive and critical to unnatural facial images even for subtle skin color bias.

In recent years, interactive operations are widely introduced into Poisson image editing to make its manipulations much easier or add more functions for various applications. J. Sun et al. [8] proposed structure propagation technique that can propagate the salient texture structure of image along user-specified curves for seamless image editing with structure characteristic remained. A. Agarwala et al. [12] developed a complete system, in which the optimal boundaries can be searched from the users designated regions for image composition.

In this paper, we propose an interactive image editing method based on Poisson equation to solve the multi-patch photometric alignment problem for facial composite robust to severe color discrepancy. For stitched image with patches of arbitrary shapes and number, a generalized form of Poisson equation with averaged color constraint is constructed and formulated...
into simultaneous linear equations. To solve the equations efficiently, a layer-based propagation algorithm is designed. With our system, users can designate any expected patch in the stitched image as the photometric reference, and the system will propagate its photometric effect onto other patches layer by layer automatically and seamlessly. Our method has well settled the tradeoff between satisfied quality and convenient operation for illumination alignment problem of composite image, and can be easily extended to image composition tasks beyond facial images.

The rest of this paper is organized as follows: the Poisson image editing technique is reviewed in Section II. In Section III and IV, we describe our Poisson equation constructing and solving methods for photometric propagation. We discuss experiments in section V and conclude in section VI.

II. POISSON IMAGE EDITING

To paste a region of interest (ROI) denoted by $\Omega$ from the source image $g$ to the target image $f^*$, the following minimization problem needs to be addressed based on the guidance field $v = \nabla g$:

$$\min_f \int_{\Omega} |\nabla f - v|^2 \quad \text{with} \quad f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

(1)

Where $\nabla = \left( \frac{\partial}{\partial x}, \frac{\partial}{\partial y} \right)$ is the gradient operator, $f$ is the resulting image, and $\partial\Omega$ is the exterior boundary of $\Omega$. The solution of (1) satisfies the associated Poisson equation with Dirichlet boundary condition:

$$\Delta f = \text{div}(v) \quad \text{over} \quad \Omega, \quad \text{with} \quad f|_{\partial\Omega} = f^*|_{\partial\Omega}$$

(2)

Where $\Delta = \left( \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \right)$ is the Laplacian operator and $\text{div}(v) = \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}$ is the divergence of $v = (u,v)$. This is the fundamental mechanism of Poisson image editing technique [7], as illustrated in Figure 1.(a).

III. INTERACTIVE PHOTOMETRIC ALIGNMENT

A. System Overview

In image composition task, the image patches coming from different source images always present inconsistent photometric intensities. We propose an interactive image editing tool in this paper, user can align the photometric effect of a pieced image according to any expected region just by clicking on that region in the division map, and then its photometric effect will be propagated onto the whole image automatically and seamlessly. Figure 2 illustrates two examples of this process on a typical facial region division map.

Based on the Poisson image editing technique, there still remain two main problems to be solved for our system: firstly, how to construct Poisson equations for multi-patch image stitching; secondly, how to organize the solving sequence efficiently among the multiple patches. We will address these two problems in the following part and next section respectively.

B. Constructing Multi-patch Poisson Solver

For the task of multi-region photometric alignment as in Figure 2, we need to extend the single guidance field problem (as in Figure 1.(a)) into multiple guidance fields occasion (as in Figure 1.(b)). Let $\Omega_i, i=1...N, N \geq 2$ denote the $i$-th ROI region, $g_i$ and $f_i$ denote the image patches segmented by $\Omega_i$ on source image $g$ and resulting image $f$ respectively. Then, our task can be described in short: re-render all $f_i$ according to guidance patch $g_i$ and stitch them together seamlessly. Therefore, we firstly generalize the objective function in (1) as follows:

$$E_m(f_i) = \int_{\Omega_i} |\nabla f_i - \nabla g_i|^2,$$

(3)

with $f|_{\partial\Omega_i} = f^*|_{\partial\Omega_i}, \forall \xi_{i,j} \subset \partial\Omega_i$

Where $\xi_{i,j}$ denotes pixel set on the boundary of any two adjacent regions $\Omega_i$ and $\Omega_j$. Let $\Omega_{\ast}$ denote the reference photometric region that may be any of one $\Omega_i$. Then $\partial\Omega_{\ast}$, the boundary between $\Omega_{\ast}$ and any other $\Omega_j$, will constitute the Dirichlet boundary condition of the Poisson equations. However, boundaries between those $\Omega_i$ are still constituted by unknown pixels.

Using the similar formulation as in (1) and (2), the solution of $\min E_m(f_i)$ satisfies the following Poisson equation:

$$\Delta f_i = \Delta g_i, \quad \text{over} \quad \Omega_i$$

(4)

with $f|_{\partial\Omega_i} = f^*|_{\partial\Omega_i}, \forall \xi_{i,j} \subset \partial\Omega_i$

Figure 1  Poisson image editing. The unknown function(s) $f_{(1,2)}$ are solved using Poisson equation under constraints of known function $f^*$ and the gradient field(s) within region(s) $\Omega_{(1,2)}$.
is the set of neighbors of any pixel \( p \), the linear equations in (5) can be written into the form of linear equation:

\[
\forall p \in \Omega, \quad \sum_{q \in N_p} f(p) - \sum_{q \in N_p} f(q) = 0
\]

With 4-connection neighbors configuration, \( |N_p| = 4 \) will hold except on the image corner (where \( |N_p| = 2 \) ) and on the image edge (where \( |N_p| = 3 \)). So the possible values of the coefficients of all unknowns in this linear equation consist of 0, ±1, 2, 3 and 4. Let vector \( x \) denote all the unknown pixels in \( \Omega \), the linear equations in (5) can be written into a compact form:

\[
Mx = d, \quad \text{with} \quad x = (f(p_1), \ldots, f(p_{|\Omega|}))^T
\]

for all \( p_k \in \Omega \).

It records the space relationship of all unknown pixels. \( d \) is a column vector with size of \(|\Omega| \times 1\). It records the known pixel values.

### C. Dealing with Severe Color Discrepancy

In facial images constituted by multiple patches, the pixel values within each patch can be assumed as the Gaussian distribution, providing the patch size is small enough. Therefore, a straightforward way to avoid severe color discrepancy in the synthesis image is to align the mean pixel value in target region by the one in reference region:

\[
E_\gamma(f_i) = \frac{1}{|\Omega|} \int_{\Omega} | f_i - g_i |^2
\]

Where \( \frac{1}{|\Omega|} \int_{\Omega} f_i \) and \( \frac{1}{|\Omega|} \int_{\Omega} g_i \) calculate the mean pixel values of the target region and reference region respectively. Minimizing \( E_\gamma(f_i) \) can prevent the whole region \( \Omega \) from global color discrepancy with no change to the gradient structure of \( g_i \). By incorporating this constraint term into (3) we arrived at the final objective function:

\[
E(f_i) = E_u(f_i) + \alpha E_\gamma(f_i)
\]

With \( \alpha > 0 \) adjusts the weight between two terms. In previous section, the minimum problem of \( E_u(f_i) \) has been formulated into an equivalent linear equations. We then have to solve the sub-problem of \( \min E_\gamma(f_i) \).

Within any \( \Omega \), since \( E_\gamma(f_i) \geq 0 \) always hold, its minimum can be obtained i.i.f the equal sign stands, that is:

\[
\frac{1}{|\Omega|} \int_{\Omega} (f_i - g_i) = 0
\]

Along with the definition of unknown vector \( x_i \) in (6), (9) can also be written into the form of linear equation:

\[
hx_i - r = 0
\]

In (10), both \( h \) and \( r \) equal to \( \frac{1}{|\Omega|} u \), where \( u \in \mathbb{R}^{|\Omega|} \) represents the unit vector. Associating the equivalent linear equations in Eqs. (6) and (10) together, the solution of problem \( \min E(f_i) \) can be finally obtained by solving the simultaneous linear system (11) using the least square method.

\[
Mx_i - d = A_i x_i - b_i = 0
\]

Where the value of parameter \( \alpha \) is proportional to the weight of constraint term \( E_\gamma(f_i) \). We will choose its value using cross validation manner in the experiments.
IV. POISSON SOLUTION PROPAGATION ALGORITHM

For the whole ROI \( \Omega \), the unknown function value \( f_i \) on any of a region \( \Omega_j \subset \Omega \) is just the solution of (11). The so obtained \( f_i \) on all the \( \Omega_j \) will constitute the final composite with the photometric effect aligned from the reference region \( \Omega \) onto the whole \( \Omega \) seamlessly.

Since each unknown region \( \Omega_i \) will generate \( |\Omega_i| \) linear equations, where \( |\Omega_i| \) denotes the number of pixels inside \( \Omega_i \). The unknowns in the so obtained simultaneous equations will not only contain pixels inside \( \Omega_i \), but pixels along boundary \( \xi_{ij}, j \neq i^* \). Therefore, the number of total unknowns will exceed \( |\Omega_j| \). Such an undetermined linear system can not get unique solution. So (11) cannot be solved separately for each individual region.

Considering this problem globally, it can be noticed that for any neighboring unknown regions \( \Omega_i \) and \( \Omega_j \), the unknowns of \( \Omega_i \) along \( \xi_{ij}, j \neq i^* \) are actually a subset of the unknown set of \( \Omega_j \), and vice versa. If associating their equations together, the number of simultaneous equations and the unknowns will be both \( |\Omega_j| + |\Omega_i| \), and unique solutions for both regions can then be achieved. Of course we can simply associate all the unknown regions together, which is also a common adoption in previous methods \([12]\). But this will cause the coefficient matrix of the simultaneous linear equations up to scale of \( \sum_{j} |\Omega_j| \times \sum_{i} |\Omega_i| \), with the computational complexity of \( O\left[ \left( \sum_{j} |\Omega_j| \right) \right] \). Although it can be reduced to \( O\left[ \sum_{j} |\Omega_j| \right] \) by using sparse matrix storage and iteration solver, it is still a big computational load for large size images.

A. Layer-based Propagation

Alternatively, a layer-based propagation algorithm is proposed here to solve this problem. Starting from the reference region \( \Omega_{ref} \), all the unknown regions \( \Omega_j \) that satisfying \( \xi_{ref,j} \neq \Phi \) are firstly searched. The so obtained \( \Omega_j \) are direct neighbors of \( \Omega_{ref} \). Their union \( \bigcup_{j} \Omega_j \) forms the first propagation layer in which the first simultaneous equation according to (11) will be constructed. The exterior border of this layer will turn into Dirichlet boundary condition for the remained regions after this layer being solved. Same procedure will be repeated to search and solve the next layer, until all the unknown regions are re-rendered. This algorithm is the process of photometric effect propagating from \( \Omega_{ref} \) to outer layers, as well as the process of the Poisson solution propagation and the Dirichlet boundary propagation to outer layers.

In our algorithm, the region set of any \( l \)-th layer is searched in this way: for any boundary pixel \( p \) in the \( (l-1) \)-th layer, if \( N_p \cap \Omega_j \neq \Phi \), where \( \Omega_j \) is any unknown region, then \( \Omega_j \) is partitioned into the \( l \)-th layer.

B. Poisson Solution in Each Layer

Assuming layer \( l \) contains \( n_l \) unknown regions \( \Omega_j \) \((j = 1 \cdots n_l)\), let \( A_j x_j = \mathbf{b}_j \) denote the linear equations within each \( \Omega_j \), where vector \( x_j = \left( f_j(1), \cdots, f_j\left( |\Omega_j| \right) \right)^T \) denotes the values of all the pixels to be solved in this region. With all \( n_l \) regions being associated, the simultaneous linear equation for layer \( l \) can be obtained as in (12), with the coefficient term \( A \) being a sparse block matrix,

\[
A x = b, \text{ with } A = \begin{pmatrix}
A_{11} & \cdots & A_{1n_l} \\
\vdots & \ddots & \vdots \\
A_{n_l1} & \cdots & A_{nn_l}
\end{pmatrix}
\] (12)

The sub-matrices \( A_{ij} \) on the diagonal here equal to the coefficient matrices \( A_{ij} \) of any \( \Omega_j \), while other sub-matrices \( A_{ij} \) \((i \neq j)\) record the constraints coming from the neighboring unknown regions within current layer. \( A_{ij} \) will equal to zero if \( \xi_{ij} = \Phi \). The unknown vector \( x \) and the constant vector \( b \) in (12) are concatenated from the corresponding terms in equations of each individual region:

\[
x = \left( x_1, x_2^T \cdots x_{n_l}^T \right)^T, \quad b = \left( b_1^T, b_2^T \cdots b_{n_l}^T \right)^T
\] (13)

Using the layer-based propagation mechanism, the linear equations in each layer will be solved independently and sequentially. Assuming totally \( L \) layers are detected in the propagation process, then the total computational complexity will be \( O\left( \frac{1}{L} \sum_{l=1}^L |\Omega_{ref}| \right) \), which is much smaller than the global association as described in the beginning of this section. Especially, when the regions number is large, our method will reduce the computational time and the memory consumption remarkably.

The linear equation of (12) in each layer can be solved theoretically by inversion or pseudo-inversion calculation. However, in real world applications, it will always become intolerable no matter on memory or speed. Iterative algorithms such as the Jacobian algorithm, Gauss-Seidel algorithm, Successive Over Relaxation (SOR) method, Multi-grid method etc. provide us more alternatives \([13]\), we used the SOR method in our experiments for its simple implementation and excellent convergence performance. The pseudo code of the complete Poisson propagation algorithm is summarized in TABLE.I.
V. EXPERIMENTS

A. Configuration

In Figure 3, some examples of the raw face images used in our experiments are shown, where obvious photometric difference and color discrepancy can be noticed. They are captured under different illumination conditions or camera parameters. These images are shape free because image warp technique is performed before image stitching to transform them into one uniform facial shape, so that they can be cut and pieced with the same division map. The facial mask in Figure 2 is used here as the division map, which serves as the ROI for our following facial composite.

B. Seamless Photometric Alignment

In our method, the parameter $\alpha$ is essential for the final composite effect. We use a cross validation manner here to determine its value. Regarding a randomly selected raw composite shown in Figure 4.(a), taking $\Omega'$ as the reference region, the photometric aligning results by our method using different $\alpha$ values are shown in Figure 4.(b)–(e). $\alpha = 0$ means no color constraint term is exploited. Obvious skin color bias can be found in patches apart from $\Omega'$ . By increasing the $\alpha$ value, the bias problem can be gradually reduced. After $\alpha \geq 2$, it reaches its limitation. We will take $\alpha = 2$ as the empirical value in our following experiments.

We then compared our method with the standard Poisson editing method and some other typical algorithms. Part of the results is shown in Figure 5 where (a) shows some raw composites randomly generated by facial patches from Figure 3. Taking different region as the reference $\Omega'$, (b) shows results from histogram equalization approach. It can eliminate the color discrepancy in a large extent among patches, but the piecing boundary remains obvious discontinuity. The standard Poisson editing is a seamless stitching algorithm, but when severe color discrepancy exists among raw patches, severe skin color bias problem will appear in the composite as in (c). This drawback is also found in (d) produced by the PhotoMontage approach [12]. This algorithm uses the average gradient along the boundary pixels as the guidance to make the composite more smooth. Our results show in (e). It can be found the photometric effect has been aligned seamlessly onto the reference region, meanwhile, more natural skin color compared to the previous algorithms can be obtained by our method.

Figure 6 and TABLE II has summarized the statistical experimental results of our method compared with the standard Poisson editing. 10 randomly generated raw

<table>
<thead>
<tr>
<th>TABLE I</th>
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<tbody>
<tr>
<td>SYNOPSIS OF THE LAYER-BASED POISSON PHOTOMETRIC PROPAGATION ALGORITHM</td>
</tr>
</tbody>
</table>

| Step0: // Initiate the variables: Designate the photometric reference region: $\Omega'$ ← $\Omega_j$ from any of the $J$ regions; The set of unknown regions: $\Gamma ← \{1, \cdots, J\} \setminus j$; While $\Gamma \neq \Phi$ Do The set of regions in current layer: $\Pi ← \Phi$; Step1: // Search the regions of current layer: For each pixel $p \in \partial \Omega'$ and each region label $i \in \Gamma$ Do If neighbors of the current pixel: $\Pi \cap \Omega_i \neq \Phi$ And $i \in \Gamma$ Do $\Gamma ← \Gamma \cup i$; $\Pi ← \Pi \cup \{i\}$; End If End For The current layer is found: $\Omega' ← \bigcup_{i \in \Gamma} \Omega_i$; Step2: // Construct the simultaneous Poisson equations in current layer: For each pixel $p \in \Omega'$ Do Construct linear equation according to (5); End For Associate all equations in $\Omega'$ into simultaneous Equation: $Ax = b$ according to (12) and (13); Step3: // Solve the simultaneous equations and re-render the regions in current layer: $x ← A^{-1}b$ is solved by SOR iterative method; For each pixel $p \in \Omega'$ Do Re-render $p$ by the Poisson solution: $f(p) ← x(p)$; End For End While |
composites with 6 different \( \Omega \) region selections make up 60 times independent piecing experiments here. For each composite, the displacement \( v \) between the average skin color value and the ground truth (average color of \( g^* \)) is defined to measure the color bias:

\[
v = \frac{1}{|\Omega|} \sum_{p \in \Omega} |f(p) - g^*(p)|
\]  

(14)

Where \( \Omega = \bigcup_{i} \Omega^{i} \) denotes the ROI on any a face as shown in Figure 2, and \( g^* \) is the source face image where reference region \( \Omega^* \) locates. Equation (14) will then be repeated on R, G, and B channels respectively, and the resulting histogram distributions of \( v \) are illustrated in Figure 6, where its X-axis is the value of \( v \) and Y-axis records the counts of occurs. Finally, their quantitative statistics are summarized in TABLE II. It can be seen that the proposed method has much smaller skin color bias than the other two methods.

![Figure 3](image3.png)

Figure 3  some raw facial images used for composite. All images are warped into uniform shape. Obvious photometric difference can be noticed among them.

![Figure 4](image4.png)

Figure 4  The impact of parameter \( \alpha \) value towards the skin color bias problem in facial composite.

![Figure 5](image5.png)

Figure 5  Comparison of 4 algorithms for the photometric alignment in facial composite. (a) raw composites and photometric reference region, (b) histogram equalization, (c) Poisson editing, (d) PhotoMontage, (e) our method. Part of results using 2 different test composites randomly selected from 60 times independent experiments are shown in 2 rows respectively.

C. Interactive Photometric Propagation

Using the method proposed in this paper, user can align the photometric effects of all the regions according to one reference region designated arbitrarily. One example of this process is demonstrated in Figure 7 where the mandible region is designated as the photometric reference \( \Omega^* \). Poisson equations within the 1st layer that is directly adjacent to \( \Omega^* \) are firstly constructed and solved. The results will be used as the reference for solving the next layer. After three layers, the dark photometric effect has been propagated from one patch onto all other patches seamlessly.

In our system, different designations of the reference region \( \Omega^* \) will lead to different photometric propagation results. In Figure 8 the left forehead region in the division map is selected as the photometric reference. Consequently, a totally different photometric re-rendering turns out from the same original pieced image.

D. Computational Performance

The main computational load of the Poisson propagation algorithm comes from solving the simultaneous linear equation of (12). In this section, we will compare the time/space performance of the proposed method with respect to the standard Poisson image editing method. The experiment is running under the environment of Matlab6.5 with a PC of PentiumIV CPU 2.66G and 1G memory.
TABLE II
QUANTITATIVE STATISTICS FOR FIGURE 6’ EXPERIMENTS

<table>
<thead>
<tr>
<th>Method</th>
<th>R channel</th>
<th>G channel</th>
<th>B channel</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Poisson Editing</td>
<td>Max 19.9</td>
<td>31.86</td>
<td>32.67</td>
<td>28.14</td>
</tr>
<tr>
<td>Mean</td>
<td>10.64</td>
<td>12.53</td>
<td>13.66</td>
<td>12.28</td>
</tr>
<tr>
<td>Photomontage method</td>
<td>Max 17.27</td>
<td>25.58</td>
<td>24.84</td>
<td>22.56</td>
</tr>
<tr>
<td>Mean</td>
<td>8.68</td>
<td>10.63</td>
<td>11.63</td>
<td>10.31</td>
</tr>
<tr>
<td>Our method</td>
<td>Max 0.73</td>
<td>0.63</td>
<td>0.68</td>
<td>0.68</td>
</tr>
<tr>
<td>Mean</td>
<td>0.26</td>
<td>0.25</td>
<td>0.28</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Figure 7 Photometric propagation for facial composite. Facial image (d) is the raw stitching image. Using region Ω as the reference, the photometric alignment results on each of the three layers’ propagation are shown in (e)~(g).

Figure 8 Photometric propagation with another direction. Using the same raw composite facial image, while starting from an altered reference region Ω’, the layer configuration will also vary as illustrated in (a)~(c). The photometric alignment results in each layer upon this new propagation route change into (e)~(g) respectively.

To reveal the relationship between the unknown pixel number and the running time to solve (12), a toy problem was tested firstly. We randomly picked a set of image patches size from 800 pixels up to 5500 pixels. The result curve was plotted in Figure 9.(a). With the increase of the pixel numbers, the running time grows exponentially. This implies that solving multiple small image patches will be more economical than solving a big one.

TABLE III
COMPARISON OF THE RUNNING TIME (IN SEC.) ON SOLVING THE POISSON EQUATION IN FIGURE 7 BY USING PLAIN FORM MATRIX STORAGE FORMAT

<table>
<thead>
<tr>
<th>Sub-sampling rate</th>
<th>Layer 1</th>
<th>Layer 2</th>
<th>Layer 3</th>
<th>Layer 1 ~ 3</th>
<th>Standard Solver</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/4</td>
<td>0.625 (s)</td>
<td>34.587 (s)</td>
<td>0.594 (s)</td>
<td>14.953 (s)</td>
<td>11.297 (s)</td>
</tr>
<tr>
<td>1/2</td>
<td>0.266 (s)</td>
<td>14.953 (s)</td>
<td>0.266 (s)</td>
<td>7.7 (s)</td>
<td>N/A</td>
</tr>
</tbody>
</table>

TABLE IV
COMPARISON OF THE RUNNING TIME (IN SEC.) AND THE STORAGE CONSUMING (IN M) ON SOLVING THE POISSON EQUATION IN FIGURE 7 BY USING THE SPARSE MATRIX STORAGE FORMAT AND DIFFERENT SAMPLING RATES

<table>
<thead>
<tr>
<th>Sub-sampling rate</th>
<th>Layer 1</th>
<th>Layer 2</th>
<th>Layer 3</th>
<th>Layer 1 ~ 3</th>
<th>Standard Solver</th>
</tr>
</thead>
<tbody>
<tr>
<td>Using Sparse Matrix</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Time</td>
<td>N/A</td>
<td>6.5s</td>
<td>35.2s</td>
<td>82.2s</td>
<td>32.6s</td>
</tr>
<tr>
<td>Space</td>
<td>N/A</td>
<td>5.4M</td>
<td>19.9M</td>
<td>482M</td>
<td>2.3M</td>
</tr>
</tbody>
</table>

We further tested the impact of layer numbers with respect to running time. A randomly selected image patch with size of 5000 pixels was equally divided into various numbers of layers. From the resulting performance curve plotted in Figure 9.(b), it can be found the running time was decreasing continuously with the increase of divided layer numbers. This also verified our propagation algorithm is more computational efficient than the standard holistic Poisson solver.

To measure the computational performance on real application of image composite, the photometric propagation experiment in Figure 7 was used here as the test bench. The raw pieced image was with the resolution of 287×390 and two sub-sampling rates were tested. Firstly, the time consumed of our algorithm with
common matrix format implementation was summarized in TABLE III. Using the three layers as configured in Figure 7.(a)-(c), our layer-based propagation solver presented less running time compared to the holistic solver, in which all the unknown regions were combined into one patch union for calculating.

TABLE IV summarized the time/space performance using the sparse matrix format in Matlab implementation. The original size image (287×390) and the 1/2 sub-sampled image were tested. In all experiments, the sparse matrix + propagation solver showed much lower cost than the common matrix + standard solver. By using the sparse matrix format, although the proposed method showed similar performance compared to the standard solver, it saved more memory expense than the standard solver. This advantage will be useful for large scale image composite task.

VI. CONCLUSION

Toward the illumination inconsistency problem in multi-patch image stitching, a layer-based propagation method is proposed to implement the photometric alignment and the interactive photometric editing for facial image composite robust to color bias problem. To do that, an extended Poisson equation with averaged color constraint is formulated. The proposed layer-based propagation algorithm can solve the equations with reduced computational complexity. Experiments on facial composite images have verified the designed function of our system.

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