Semi-supervised Parametric Real-world Image Harmonization

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\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig1.png}
\caption{Visual comparisons between state-of-the-art harmonization methods IHT [9], Harmonizer [14], and ours. Our model is fully parametric. This gives artists full posterior control over the final composite, makes runtime efficient for high-resolution real-world inputs and regularizes training. Our model predicts global RGB curves and a local shading map (right). Benefiting from the novel dual-stream semi-supervised training strategy, our method (right) produces more realistic harmonized images on real-world composites (left). This new training strategy, together with the shading map, makes it the first harmonization method to address local tonal adjustments, such as shading the face according to the sun’s direction (top) or selectively darkening the part of the dog inside the cave (bottom).}
\end{figure}

Abstract
Learning-based image harmonization techniques are usually trained to undo synthetic random global transformations applied to a masked foreground in a single ground truth photo. This simulated data does not model many of the important appearance mismatches (illumination, object boundaries, etc.) between foreground and background in real composites, leading to models that do not generalize well and cannot model complex local changes. We propose a new semi-supervised training strategy that addresses this problem and lets us learn complex local appearance harmonization from unpaired real composites, where foreground and background come from different images. Our model is fully parametric. It uses RGB curves to correct the global colors and tone and a shading map to model local variations. Our method outperforms previous work on established benchmarks and real composites, as shown in a user study, and processes high-resolution images interactively.

Code, and project page available at: https://kewang0622.github.io/sprih/.

1. Introduction
Image harmonization [12, 22, 23, 26, 28, 32] aims to iron out visual inconsistencies created when compositing a foreground subject onto a background image that was captured under different conditions [18, 32], by altering the foreground’s colors, tone, etc., to make the composite more realistic. Despite significant progress, the practicality of today’s most sophisticated learning-based image harmonization techniques [3, 4, 9, 10, 13, 14, 16, 32] is limited by a severe domain gap between the synthetic data they are trained on and real-world composites.

As shown in Figure 2, the standard approach to generating synthetic training composites applies global transforms
Figure 2. **Domain Gap between synthetic and real-world composites.** The existing synthetic composites [4] (left), generated by applying global transforms (e.g., color, brightness), are unable to simulate many of the appearance mismatches that occur in real composites (right). This leads to a domain gap: models trained on synthetic data do not generalize well to real composites. In real composites (right), the foreground and background are captured under different conditions. They have different illuminations, the shadows do not match, and the object’s boundary is inconsistent. Such mismatches do not happen in the synthetic case (left).

We argue that using realistic composites for training is essential for image harmonization to generalize better to real-world use cases. Because collecting a large dataset of artist-created before/after real composite pairs would be costly and cumbersome, our strategy is to use a semi-supervised approach instead. We propose a novel dual-stream training scheme that alternates between two data streams. Similar to previous work, the first is a supervised training stream, but crucially, it uses artist-retouched image pairs. Different from previous datasets, these artistic adjustments include global color editing but also dodge and burn shading corrections and other local edits.

The second stream is fully unsupervised. It uses a GAN [8] training procedure, in which the critic compares our harmonized results with a large dataset of realistic image composites. Adversarial training requires no paired ground truth. The foreground and background for the composite in this dataset are extracted from different images so that their appearance mismatch is consistent with what the model would see at test time.

To reap the most benefits from our semi-supervised training, we also introduce a new model that is fully parametric. To process a high-resolution input composite at test time, our proposed network first creates a down-sampled copy of the image at 512 \( \times \) 512 resolution, from which it predicts global RGB curves and a smooth, low-resolution shading map. We then apply the RGB curves pointwise to the high-resolution input and multiply them by the upsampled shading map. The shading map enables more realistic local tonal variations, unlike previous harmonization methods limited to global tone and color changes, either by construction [14, 16, 31] or because of their training data [4].

Our parametric approach offers several benefits. First, by restricting the model’s output space, it regularizes the adversarial training. Unrestricted GAN generators often create spurious image artifacts or other unrealistic patterns [36]. Second, it exposes intuitive controls for an artist to adjust and customize the harmonization result post-hoc. This is unlike the black-box nature of most current learning-based approaches [3, 4, 9, 10], which output an image directly. And, third our parametric model runs at an interactive rate, even on very high-resolution images (e.g., 4k), whereas several state-of-the-art methods [4, 9, 10] are limited to low-resolution (e.g., 256 \( \times \) 256) inputs.

To summarize, we make the following contributions:

- A novel dual-stream semi-supervised training strategy that, for the first time, enables training from real composites, which contains much richer local appearance mismatches between foreground and background.
- A parametric harmonization method that can capture these more complex, local effects (using our shading map) and produces more diverse and photorealistic harmonization results.
- State-of-the-art results on both synthetic and real composite test sets in terms of quantitative results and visual comparisons, together with a new evaluation benchmark.

2. Related works

**Image harmonization.** Traditional image harmonization methods mainly focus on adjusting the low-level appearance statistics (e.g., color statistics, gradient information) between the foreground objects and the background [12, 22, 23, 26, 28, 32]. Supervised learning-based approaches have been proposed and shown notable success [3, 4, 9, 10, 29, 37] by learning image harmonization from synthetic training pairs, for instance, iHarmony Dataset [4]. Works as DIH
Figure 3. Overview of semi-supervised dual-stream training strategy. To bridge the domain gap, our proposed semi-supervised dual-stream training strategy alternates between two training streams: a) Supervised training with artist-retouched composite image pairs (left). Artist adjustments include global color editing, shading correction, and other local edits. b) Unsupervised adversarial training with real-world composite images (right). It uses a GAN [8] training procedure, comparing our harmonized results with a large dataset of composite "real" images (see § 3.2 for details). The foreground and background for the composite are from different images, so the appearance mismatch is consistent with what we see at test time.

[29], DovNet [4], IHT [9], Guo et al. [10] consider the image harmonization task as a pixel-wise image-to-image translation task, and are limited to low-resolution inputs (typically $256 \times 256$) due to computational inefficiency. Recent work extended image harmonization to high-resolution images by designing parametric models [3, 14, 16, 31]. To name a few, Liang et al. learns the spatial-separated RGB curves for high-resolution image harmonization. Ke et al. [14] directly predicts the filter arguments of several white-box filters. In all of those approaches, synthetic training pairs are generated by applying global transforms to the masked foreground regions and hence do not simulate mismatch in illumination, shadows, shading, contact, etc., that happen in real-world composite images. Therefore, due to the synthetic training data and model construction [14, 16], previous works are limited to global tone and color changes. In contrast, our model is trained on real-world composite images and artist-retouched synthetic images, which enables us to model richer image edits and produce more compelling results on real composites.

Efficient and high-resolution image enhancement. There has been a wide range of research focusing on designing efficient and high-resolution image enhancement algorithms [6, 7, 17]. Gharbi et al. [6] introduced a convolutional neural network (CNN) that predicts the coefficients of a locally-affine model in bilateral space from down-sampled input images. The coefficients are then mapped back to the full-resolution image space. Zeng et al. [34] directly learns 3D Lookup Tables (LUTs) for real-time image enhancement. In our application, image harmonization can be considered as a background-guided image enhancement problem. Thus, inspired by [6, 34], we design a network that directly predicts the coefficients of RGB curves (piece-wise linear function) from down-sampled composite inputs. We then apply the RGB curves pointwise to the high-resolution input without introducing extra computation costs.

Image-based relighting. Image-based relighting approaches [19, 21, 25, 33] focus on modifying the input lighting conditions and local shading to generate convincing composite results. However, recent relighting methods mainly focus on portraits and struggle to generalize to other objects, as Light-stage capture is limited to portraits and not diverse objects [5]. With a similar idea of incorporating local shading edits but a different approach, our method embeds the shading layer into a network and trains on composite image datasets without explicitly leveraging scene representations (geometry, materials, lighting) and using full relighting models.

3. Method

Our image harmonization method corrects the foreground subject in a rough composite to make the overall image look more realistic using a new parametric model (§ 3.1) that can be applied to real-world high-resolution images efficiently. Previous harmonization techniques train on synthetically-generated composite pairs [4], where the model’s input is a global transformation of a ground truth image within a foreground subject mask. The colors are often unnatural, the mask boundary is close to perfect, and there is no mismatch in appearance, illumination, or low-level image statistics since both foreground and background come from the same image. As a result, models trained on such data generalize poorly. Our method addresses this crucial issue using a novel dual-stream semi-supervised train-
Global color correction curves. In our first high-resolution processing stage $t_1$, we apply the predicted global RGB curves for color correction. These curves are parameterized as 3 piecewise linear curves with 32 control points and are applied independently to each color channel, resulting in a set of 2D coordinates, $\theta_1 \in \mathbb{R}^{32 \times 2 \times 3}$. The output color for each channel is interpolated between adjacent control points. We employ a ResNet-50-based network \cite{he2016deep} to predict these parameters from $[C_{lr}, B_{lr}, M_{lr}]$. The curve application, a per-pixel operation, allows for efficient computation at any resolution.

Local low-frequency shading map. Our second stage $t_2$ multiplies the image with a low-frequency grayscale shading map, to model local tonal corrections. It is applied to the output of the first stage. We constrain the shading map to only model low-frequency change by first generating $\theta_2$ at a low resolution $64 \times 64$, then upsampling, and passing a single convolution layer at $512 \times 512$ to correct upsampling artifacts. It is produced by a modified U-Net \cite{ronneberger2015u} with large receptive field, given the low-resolution buffers $[C_{lr}, B_{lr}, M_{lr}]$, together with the output of the color-correction stage at low-resolution $t_1(C_{lr}, M_{lr}; \theta_1)$. At test time, we upsample the low-resolution shading map to the original high-resolution and multiply it pointwise with the color-corrected image to obtain our final harmonized composite:

$$O = t_1(C, M; \theta_1) \odot \text{upsample}(t_2).$$

### 3.2. Dual-stream semi-supervised training

Our semi-supervised training strategy aims to alleviate the generalization issues that plague many state-of-the-art harmonization models, as shown in Figure 2. During a single training stage, our approach equally samples two data streams and optimizes a distinct objective for each of them. The first stream uses input/output composite pairs similar to previous work, except that we only use artist-created image transformations instead of random augmentations. The second is unsupervised. This allows us to use more realistic images obtained by compositing foreground and background from unrelated images, for which no ground truth is easily obtainable. For the supervised stream, the objective combines $\ell_1$ loss and adversarial loss, while the unsupervised stream solely utilizes adversarial loss.

Supervised training using retouched images. The first stream is fully supervised. Unlike previous work, we use images retouched by artists rather than mostly relying on random augmentations. We refer to this dataset as Artist-Retouched in the rest of the paper. Artists were allowed to use common image editing operations such as global luminosity or color adjustments, but also local editing tools like brushes, e.g., to alter the shading. Specifically, we collected $n = 46173$ before/after retouching image pairs

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\footnote{https://youtu.be/g3qe4rDw1XU}
\{I_i, O_i\}_{i=1,\ldots,n}$, with the mask for one foreground object $M_i$ for each pair. From each triplet, we can create 2 input composites for training: one with only the foreground retouched $M_i \cdot O_i + (1 - M_i) \cdot I_i$, and the other with only the background is retouched $M_i \cdot I_i + (1 - M_i) \cdot O_i$. Since our harmonization model only alters the foreground, we use the unedited image $I_i$, and the retouched image $O_i$, as ground truth targets for these input composites, respectively.

When sampling training data from this stream, we optimize our model’s parameters to minimize the sum of an $\ell_1$ reconstruction error $L_{\text{rec}}$ between the ground truth and our model output, and an adversarial objective [8]

$$\lambda L_{\text{rec}} + (1 - \lambda) L_G,$$

with $\lambda$ balances the two losses. For our experiments, $\lambda$ is empirically set to 0.92. The generator, our parametric image harmonization model, is trained to produce outputs that cannot be distinguished from “real” images. We use a U-Net discriminator [30] $D$ to make per-pixel real vs. fake classifications. Since our data formation model assumes the background is always correct, our discriminator is trained to predict the inverted foreground mask $1 - M$. That is when shown “fake” images, i.e., the background pixels have label 1 and the foreground 0. For the “real” class, the target is all an all-1s map. So the discriminator loss is given by:

$$L_D = -E_{I_{\text{real}}} \log(D(I_{\text{real}}))$$
$$- E_{I_{\text{fake}}} \log((1 - M) - D(I_{\text{fake}})).$$

The generator loss is:

$$L_G = -E_{I_{\text{fake}}} \log(D(I_{\text{fake}})).$$

To further increase the training diversity, we randomly augment the foreground brightness on the fly without retouching the color.

**Unsupervised training with real composites.** Our second training stream is unsupervised. It uses randomly generated composites that are representative of real-world use cases but for which no ground truth is available. To properly reproduce the appearance mismatch in real applications, we create these composites as follows: We start from a dataset of $m$ images $\{I_i\}_{i=1,\ldots,m}$, each with a foreground object mask $M_i$, and a background $B_i = (1 - M_i) \cdot I_i$. As preprocessing, we dilate the foreground mask by 30 pixels and inpaint the corresponding area in the background image using a pre-trained inpainting network (we use LaMa [27]). Then during training, we sample two images $i$ and $j$ and create a composite by pasting the foreground $j$ onto the inpainted background of $i$:

$$C_{ij} := F_j \cdot M_j + \text{inpaint}(B_i, M_i) \cdot (1 - M_j).$$

The triplet $\{C_{ij}, \text{inpaint}(B_i, M_i), M_j\}$ is passed as input to our model. Figure 3b illustrates the process. $F_j$ is translated and rotated from the original foreground so that it’s maximally contained within $F_j$’s bounding box.

With no ground truth available when sampling composites from this data stream, we only optimize the adversarial loss $(1 - \lambda) L_G$, as defined in Eq. (4), where again the fake samples $I_{\text{fake}}$ are the outputs of our model.

The discriminator is trained with Eq. (3), where $I_{\text{real}}$ is not a real composite, but is obtained by masking the foreground subject $F_i$, inpainting the background $B_i$, and pasting the foreground back onto the same image, i.e.

$$I_{\text{real}} := F_i \cdot M_i + \text{inpaint}(B_i, M_i) \cdot (1 - M_i).$$

This is similar to how we produce a composite of two images $i$ and $j$, expect that we only use one image, $i$. This alteration of the “real” class is to prevent the discriminator from using the inpainting boundary region as a strong cue to discriminate between our model output and real images, which leads to collapse in the GAN training.

GAN training is known to be unstable or cause image artifacts [36], but because our parametric harmonization model adjusts color curves and adds low-resolution shadows, instead of predicting pixels directly, it has a strong regularizing effect, which prevents the GAN training to degenerate and cause spurious artifacts in the output image. We use the same discriminator (and generator) in both streams.

**4. Experiments**

We compare our parametric image harmonization model with state-of-the-art methods on established benchmarks (§ 4.1), as well as a test subset of Artist-Retouched dataset. Furthermore, we demonstrate our superior performance on real-world harmonization tasks via a user study and qualitative comparisons on real composites (§ 4.2). Ablation studies highlight the advantages of our semi-supervised training approach and our parametric model’s components (§ 4.3). More results can be found in the supplementary.

**Evaluation metrics:** For quantitative comparisons with ground truth, we report performances by Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS) [35]. PSNR is measured in dB and calculated as: $\text{PSNR} = 10 \log_{10} \frac{255^2}{\text{MSE}}$.

**Implementation details:** Our models are implemented in PyTorch [20] and trained on an NVIDIA A100 GPU using the Adam optimizer [15] for 80 epochs, with a batch size of 8 and an initial learning rate of $4 \times 10^{-5}$, decayed by a factor 0.2 every 20 epochs. Our model has 93M parameters (23M for stage $t_1$, 70M for stage $t_2$). Our model can run at an interactive rate where inference at 512x512 resolution takes on average (100 independent runs) 377 ms on an Apple M1 CPU, and 48.6 ms on an NVIDIA A100 GPU.

**4.1. Quantitative comparisons on paired data**

We compare our method with three recent methods, DovNet [4], Image Harmonization with Transformer
Figure 5. **Representative visual comparisons between state-of-the-art harmonization results.** We compared our method with composite, DovNet [4], IHT [9], and Harmonizer [14], and ground truth on both a) **Artist-Retouched** synthetic dataset and b) RealHM real-world composite dataset. Red boxes indicate the foreground subject in the composite image. The ground truth for RealHM benchmark [13] is expert-annotated harmonization results. Our results show better visual agreements with the ground truth in terms of color harmonization (rows 1,2 and 4) and shading correction (row 3).

We report metrics at both at $256 \times 256$ and $2048 \times 2048$ resolution on the HAdobe5k high-resolution subset of iHarmony. Like our parametric approach, Harmonizer can process high-res images, but the other two methods are limited to $256 \times 256$ inputs. So, for high-res comparison, we bilinearly downsample the input to DovNet and IHT, process the image, then bilinearly upsample the result before computing the metrics. Despite its simplicity, our parametric model consistently outperforms or matches the more complex baselines. Results are summarized in Table 1.

The iHarmony dataset is dominated by unrealistic synthetic image augmentations (71%), so we also evaluate our results on more realistic retouches from human experts. The two datasets we use for evaluation are a testing split of our Artist-Retouched dataset, introduced in Section 3.2, containing 1000 before/after pairs, and the RealHM [13] benchmark, containing 216 real-world high-resolution compos-
datasets. As shown in Figure 5, our method produces more realistic results, closer to the ground truth.

### 4.2. Evaluation on real composite images

Our semi-supervised training procedure allows us to train on realistic composites, where foreground and background come from different sources. Just like it limits the training potential of harmonization methods, using paired data created from a single ground truth image for evaluation is unsatisfying because it is not representative of real-world use cases (Fig. 2). So, we demonstrate the practical effectiveness of our method in a user study with real composites. For qualitative evaluation, we also created a set of 40 high-resolution real composite images with reference images. For quantitative evaluation, we also created a set of 40 high-resolution real composite images with reference images.

#### User Study.

Our user study follows a 2 alternatives forced choice protocol [35], comparing our model with DovNet [4], IHT [9], and Harmonizer [14]. We selected 60 real composites from the RealHM dataset [13], making sure there were no duplicate foregrounds or backgrounds. Since RealHM primarily focuses on portrait images, we also created 40 non-portrait real composites using free-to-use images from Unsplash 2, giving us a total of 100 real composite images. Each of our results is compared with the unaltered input composite and the three baseline results, which gives 100 × 4 = 400 image pairs to compare in total, which we submitted for evaluation to a pool of subjects on Amazon Turk 3. Each participant was shown 50 image pairs and, for each pair, they were asked to “select which image looks more plausible”. To ensure the quality of the responses, each subject was also shown 10 ‘sentinel’ testing pairs composed of a real natural image and an extremely off-retouch image (e.g., where the image is all green). This helped us filter low-quality participants, such as users that always click ‘left’ to try and game the MTurk reward. After filtering, we obtained pair-wise comparison results from 70 subjects, contributing a total of 3500 comparisons. To analyze these results, we follow previous work [3,4,14], and use the Bradley-Terry (B-T) [1] model to derive the global ranking of all methods. We normalize the B-T scores such that the sum of the scores equals one across methods. Table 3 summarizes the results. It shows that our method achieves the highest B-T score, outperforming all the baselines, indicating our approach compares favorably in real-world image harmonization.

#### Real composites with captured reference.

Figure 6 shows two representative examples of real composite results (see supplemental for more). For this qualitative comparison, we created a dataset of 40 high-resolution real-composite images with reference images by capturing a fixed set of foreground objects against multiple backgrounds, as well as a ‘background-only’ image. By segmenting the foreground object from one photo and pasting onto the ‘background-only’ image of another, we get an input composite for our model. The captured photo of the same object in the same background scene (placed at roughly the same location) acts as qualitative reference. Compared to other approaches, our results are visually closer to the captured reference.

### 4.3. Ablation studies

We assess the advantages of our semi-supervised dual-stream training approach, contrasting it with traditional supervised training, while also examining the effects of our global RGB curve module and shading map. We conduct the comparisons on RealHM [13] at 2048 × 2048, comparing our full method (dual-stream training + two-stage model) with: 1. Supervised training only (Stream 1) + global curves only; 2. Supervised training only (Stream 1) + two-stage parametric model; 3. Dual-stream training + global curves module only. We report quantitative metrics (MSE and PSNR), and the B-T score from a user study (similar to § 4.2, but with 68 subjects). Table 4 and Figure 7 summarize our findings, revealing that our shading map and dual-stream training strategy substantially enhance realism.

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**Table 2. Quantitative Comparison on RealHM benchmark and Artist-Retouched dataset.** Our approach outperforms other methods in all four metrics.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>MSE ↓ PSNR ↑</th>
<th>SSIM ↑</th>
<th>LPIPS ↓</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Artist-Retouched</td>
<td>239.1</td>
<td>29.42</td>
<td>93.84</td>
</tr>
<tr>
<td></td>
<td>Harmonizer [14]</td>
<td>231.4</td>
<td>27.40</td>
<td>94.56</td>
</tr>
<tr>
<td></td>
<td>DovNet [4]</td>
<td>225.1</td>
<td>26.72</td>
<td>92.00</td>
</tr>
<tr>
<td></td>
<td>IHT [9]</td>
<td>264.0</td>
<td>26.48</td>
<td>92.46</td>
</tr>
<tr>
<td></td>
<td>Ours</td>
<td>170.1</td>
<td>29.79</td>
<td>94.56</td>
</tr>
<tr>
<td>RealHM</td>
<td>Composite</td>
<td>404.4</td>
<td>25.88</td>
<td>94.70</td>
</tr>
<tr>
<td></td>
<td>DovNet [4]</td>
<td>225.1</td>
<td>26.72</td>
<td>92.00</td>
</tr>
<tr>
<td></td>
<td>IHT [9]</td>
<td>264.0</td>
<td>26.48</td>
<td>92.46</td>
</tr>
<tr>
<td></td>
<td>Harmonizer [14]</td>
<td>231.4</td>
<td>27.40</td>
<td>94.86</td>
</tr>
<tr>
<td></td>
<td>Ours</td>
<td>153.3</td>
<td>28.34</td>
<td>95.51</td>
</tr>
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**Table 3. User Study Results.** B-T scores of composite image, DovNet [4], IHT [9], Harmonizer [14] are calculated on 100 real composite images. Our approach ranks first, suggesting superior real-world performance.

<table>
<thead>
<tr>
<th>Methods</th>
<th>B-T Score ↑</th>
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<tbody>
<tr>
<td>Composite</td>
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</tr>
<tr>
<td>DovNet [4]</td>
<td>0.1342</td>
</tr>
<tr>
<td>IHT [9]</td>
<td>0.2350</td>
</tr>
<tr>
<td>Harmonizer [14]</td>
<td>0.2257</td>
</tr>
<tr>
<td>Ours</td>
<td><strong>0.3025</strong></td>
</tr>
</tbody>
</table>

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2https://unsplash.com/
3https://www.mturk.com/
Figure 6. **Real composite harmonization results with captured reference.** The composite is obtained by pasting the foreground subject, from a different photo (not shown) onto the background (left). The reference (right) is obtained by physically placing the foreground subject in the background scene and taking a photo. We compare our method with IHT [9], and Harmonizer [14]. Our results show better visual agreement with the captured reference (best viewed by zooming on the digital preprint).

compared to the curve-only, fully-supervised model.

<table>
<thead>
<tr>
<th>Stream 1</th>
<th>Global</th>
<th>Shading</th>
<th>MSE</th>
<th>PSNR</th>
<th>B-T score</th>
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</thead>
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<td>✓</td>
<td>-</td>
<td>291.4</td>
<td>26.32</td>
<td>0.201</td>
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<td>268.3</td>
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<td>✓</td>
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<td>✓</td>
<td>223.8</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td><strong>153.3</strong></td>
<td>28.34</td>
<td><strong>0.252</strong></td>
</tr>
</tbody>
</table>

Table 4. **Ablation study results of training strategies and parametric model.** We compare our semi-supervised training strategy (Stream 1 + Stream 2) with supervised training (Stream 1) and compare our two-stage model (Global Curves + Shading map) versus the model with only the global curve module. MSE and PSNR are used for quantitative comparisons, and the B-T score is calculated from user study results.

As reported in Table 4, we observe that the dual-stream training strategy outperforms supervised training (row 3 and 4 v.s. row 1 and 2) in terms of both quantitative metrics and B-T score, which demonstrates the benefits of our proposed dual-training strategy in real-world applications. Inspecting the results in Figure 7, we observe that the dual-training strategy (column 4 and 5) brings advantages in color-harmonization when there is a strong foreground-background color mismatch.

On the other hand, as shown in Table 4 row 3 v.s. row 4, our proposed two-stage parametric model outperforms the global curve-only model by a large margin on RealHM benchmark, reducing the MSE by 30%. Furthermore, as shown in Figure 7, our full model (last column) includes both color harmonization and local shading to the results, achieving more plausible and harmonious results.

To better visualize the roles of our two-stage parametric model, Figure 8 shows the intermediate results as well as the parametric outputs (global curves and shading map) of a representative example. The global curves module harmonizes the global tone of the foreground sculpture and matches it with the background scene, while the shading map module refines local adjustments to harmonize the sculpture’s shading with the lighting environment.

Figure 7. **Visual comparison of ablations.** Our full pipeline (right) shows more color-harmonious results than supervised training-only models (columns 2 and 3). Our local shading map adjusts local shading and produces more natural outputs (compare columns 4 and 5).

5. **Conclusion**

In this work, we propose a novel semi-supervised dual-stream training strategy to bridge the training-testing domain gap and mitigate the generalization issues that limit previous works for real-world image harmonization. Our method leverages high-quality artist-created image pairs and unpaired realistic composites to enable richer image edits for real-world applications. Besides, we introduce a new two-stage parametric model (Global RGB Curves and shading map) to reap the most benefits from our training strategy and, for the first time, enable local editing effects with learned shading map. Our method outperforms other state-of-the-art methods on established benchmarks and real composites. Furthermore, our training strategy has the potential to generalize to a wider range of image harmonization operations (e.g., matching the noise, harmonizing the boundaries, adding cast shadows). As a future work, we would like to include more attributes in our models and further improve the performance of real-world image harmonization.
References


