Learning Intrinsic Images for Clothing

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Abstract—Reconstruction of human clothing is an important task and often relies on intrinsic image decomposition. With a lack of domain-specific data and coarse evaluation metrics, existing models failed to produce satisfying results for graphics applications. In this paper, we focus on intrinsic image decomposition for clothing images and have comprehensive improvements. We collected ClothIntrinsics, a clothing intrinsic image dataset, including a synthetic training set and a real-world testing set. A more interpretable edge-aware metric and an annotation scheme is designed for the testing set, which allows diagnostic evaluation for intrinsic models. Finally, we propose ClothInNet model with carefully designed loss terms and an adversarial module. It utilizes easy-to-acquire labels to learn from real-world shading, significantly improves performance with only minor additional annotation effort. We show that our proposed model significantly reduce texture-copying artifacts while retaining surprisingly tiny details, outperforming existing state-of-the-art methods.

Index Terms
Computer Vision, Intrinsic Decomposition.

1 INTRODUCTION

Analysis and reconstruction of human clothing texture is an important task for computer vision and computer graphics, yet still receiving little specialized attention. In recent works, intensive research efforts have been focused on analysis of human appearance, e.g., reconstruction of 3D human \cite{1, 2, 3} and editing or synthesis of human characters \cite{5, 3}. Many of these methods leverage intrinsic image decomposition \cite{1} and related techniques like shape from shading \cite{6} to decompose texture information into reflectance, geometry and lighting information. As a fact that clothing covers most of the surface area of people in daily life, it is vital to focus on clothing texture.

In this paper, we consider the problem of intrinsic image decomposition for human clothing. Driven by the real-world applications like image editing and benefits for other vision tasks such as 3D reconstruction and image segmentation, intrinsic image decomposition was extensively studied but remains a challenging task due to its ill-posed nature. It aims to decompose a given image $I$ into corresponding intrinsic images, usually the reflectance image $R$ encoding the surface albedo and the shading image $S$ encoding illumination conditions, satisfying Hadamard product $I = R \odot S$.

Early work designed energy terms based on priors and formulated the task as an energy minimization problem \cite{7, 8, 9, 10, 11, 12, 13}. However, they usually suffer from large computational cost, and the proposed priors are not always true due to the complex conditions of wild images. An attractive alternative is to exploit the powerful CNNs and learn the decomposition in a data-driven manner \cite{14, 15, 16, 17, 18, 19, 20}. However, different from other vision tasks, intrinsic images are extremely hard to annotate. Existing largescale datasets are either synthetic data with dense groundtruth \cite{17, 20, 21, 22} or real world images with sparse annotation \cite{23, 24}. With the data-hungry bottleneck, efficient usage of diverse data sources \cite{25, 26, 27} for indirect supervision becomes more important.

Recent state-of-the-art methods with higher benchmark scores still suffer from severe texture-copying artifacts, stopping them from real world applications. The bottleneck mainly lies in metric and data. With research progress in this field, existing popular evaluation metrics \cite{23, 24, 28} can easily get cheated and no longer truly reflect real performance \cite{16}. Models with better quantitative scores may perform qualitatively worse, making it urgent to have a more expressive metric. For the data-hungry bottleneck, to gain enough supervision for this ill-posed task, it’s essential to intelligently utilize diverse data sources.

In this paper, we address the weaknesses mentioned above and aim to improve the performance on the challenging clothing images. First, to relieve the data-hungry situation of clothing intrinsic images, we collected ClothIntrinsics dataset, with a rendered synthetic clothing image training set and a testing set with real world clothing images. Professional software for clothing design \cite{29} is used to simulate as realistic as possible clothing models. Second, we carefully designed an annotation scheme and propose a new edge-aware metric to evaluate intrinsic image decomposition models. It targets at common artifacts on real world images and provide interpretable and diagnostic feedback. Third, we propose ClothInNet, a simple but effective model for clothing intrinsic image decomposition. In this model, we incorporate the large number of easy-to-acquire single-color clothing images as additional supervision sources. These images reflect the probability distribution of real-world shading data, which is learned by the network in an adversarial manner. Additionally, a novel loss term is proposed to apply local gradient constraint on reflectance images and significantly improves performance.

The contribution of this paper can be summarized as:

- a clothing intrinsic image dataset, including a synthetic training set and a real world testing set (Sec. 3),
- a diagnostic metric to evaluate intrinsic image decomposition models (Sec. 4),
- a model to distil real-world shading distribution and carefully designed loss terms to apply exclusive gradient constraints on albedo (Sec. 5).
2 RELATED WORK

Intrinsic Image Decomposition Methods. Intrinsic image decomposition algorithms can be roughly divided into two categories: (1) optimization algorithms based on hand-crafted priors and (2) data-driven learning-based methods. Early methods usually formulate this task as an optimization problem [7, 8, 9, 10, 11, 12, 13, 14, 15, 16]. The main idea is to design a specific energy function with prior knowledge observed from image data, and then solve for the intrinsic images by minimizing the energy function. But real-world images can not fully meet these hand-crafted priors, and thus severe artifacts would occur. With fruitful achievements in other vision tasks, a promising alternative is to learn data-driven features, leveraging the powerful CNNs for feature extraction [14, 15, 16, 18, 19, 20]. These works generally consumes RGB images as input and uses a CNN to predict one or both intrinsic images. Proposed methods like mirror-link architecture [15], post-processing [16], intermediate representations [20] and adversarial module [33] are shown to improve the results. To handle the scarcity in the amount and domain of annotated data, recent research shifts the focus to indirect sources of supervision, including self-supervision [25], shared modules across datasets [18], differentiable renderer [26, 27], multiview images [28, 29] and multi-illumination sequences depicting the same scene [26, 30, 31]. However, current state-of-the-art models still generates severe artifacts for richly textured clothing images. The major problem is that we can’t densely annotate real-world images, thus lacking the knowledge of real-world intrinsic images. Our proposed method utilizes clothing priors to learn real-world shading distribution and proposes a novel gradient constraint loss to address this.

Intrinsic Images Datasets. Unlike other vision tasks, it’s difficult to obtain largescale densely annotated intrinsic images, as people can’t directly annotate the absolute value of reflectance and shading. Existing largescale datasets lie in two categories: (1) real-world images with sparse annotation and (2) synthetic data with dense groundtruth. Intrinsic Images in the Wild (IIW) dataset [23] provides sparse annotation for the pairwise comparison of reflectance on real world scene images. Shading Annotations in the Wild (SAW) dataset [24] provides additional sparse shading annotation on the same image data. However, due to the sparse labeling, the data itself is difficult to train a high-performance CNN model [14, 15]. Synthetic datasets such as MPI Sintel [21], ShapeNet [41] and CGIntrinsics [20] are also popular for training CNNs with dense supervision. But synthetic data essentially suffer from a domain gap and will affect the performance on real world data. As far as we know, CloIntrinsics dataset we propose in this work is the first intrinsic image dataset in clothing domain. With diverse shape deformation, lighting and texture, CloIntrinsics improves current models to produce tightly fitted predictions.

Intrinsic Image Metrics. In addition to qualitative comparison, quantitative metrics on real world datasets facilitate evaluation and comparison of intrinsic image decomposition algorithms. MIT Intrinsic Images dataset [28] provides dense groundtruth intrinsic images for 20 objects, which enables quantitative comparison of existing algorithms. It uses scale-invariant mean square error as the quantitatively metric. For real-world scene images, IIW dataset [23] employs weighted human disagreement rate as a metric for reflectance, which tells how well the predicted results agrees with the sparse human annotation. SAW dataset [24] classifies the shading into smooth and non-smooth, and uses precision-recall curve to evaluate the results. These existing metrics are coarse and lack interpretable evaluation on edge performance. We contribute an annotation scheme and metric to address these problems.

3 CLOINTRINSICS DATASET

To relieve the data-hungry situation and improve the relatively rough evaluation metrics for intrinsic models, we propose Clothing Intrinsic Images (CloIntrinsics) Dataset, including a synthetic training set and a real-world testing set.

3.1 Synthetic Training Set

Although largescale synthetic datasets for animated film [21] and indoor scenes [20] exist, we believe clothes generally have different priors in the shape deformation and texture patterns, and the in-domain data will surely improve the performance of intrinsic image decomposition models. The key is to render as realistic as possible clothing data. We choose to use fashion design software CLO3d [29], which produce realistic 3D clothing models with garment flats, and render the 3D models with Blender [42]. To simulate real world conditions better, as shown in Fig. 1, the training set contains diversity in the following aspects.

Shape. The variety of clothing shapes generally comes from different clothing types, and the shape deformation causes by the wearer’s poses. To cover common clothing types like T-shirt, jacket, dress, suit, etc., CloIntrinsics collects 80 3D clothing models designed by artists. To include diverse wrinkle patterns, we change the poses of avatars and simulate the deformation of clothing. In this way, it collects diverse shape patterns for clothing. As a further augmentation, we render these models in different viewpoints to get more diverse images.

Reflectance. The complex texture is among the challenges for clothing intrinsic image decomposition and it’s vital to render a dataset with diverse texture. To address this, we build a database with around 200 texture patterns. As fashion design software like CLO3d designs clothing with garment flats, we change the texture pattern of garment flats for each 3D clothing models, and thus increase diversity in reflectance.

Lighting. Real world images generally contain complex lighting conditions. In addition to global ambient lights, we generate random light sources during rendering to improve the complexity of lighting conditions. The light sources consist of one hemisphere lighting and 10 to 20 point lights randomly sampled on the upper hemisphere, with random intensity.

The data generation pipeline is shown in Fig. 1. We first collect 3D clothing models designed by artists. We then put them on avatars and simulate the shape deformation caused by pose changes. Different texture patterns are used to include diverse reflectance map. We finally render the
models with different viewpoints and lighting conditions. With the settings above, we finally raytraced 5K clothing images with paired intrinsic components at the resolution of 1024x1024.

### 3.2 Real World Testing Set

To convincingly reflect the real-world performance, we choose to evaluate our model on real world clothing images instead of synthetic data. We randomly select 500 clothing images from Paper Doll Dataset [43], and ask human experts with knowledge background in intrinsic images to annotate regions and edges of interest. The proposed edge-aware metric significantly improves the interpretability and expressiveness of existing metrics. The details are included in Sec. 4 below.

### 4 Edge-Aware Metric

The task of intrinsic image decomposition requires to distinguish whether the local pixel value changes, i.e. edges, are caused by the change of reflectance or shading. Also, the edge performance of intrinsic models is crucial in many graphics applications, and deserves special attention. However, current popular evaluation metrics are not able to evaluate edge performance in an interpretable way, and thus not expressive to show how models perform against artifacts. For instance, the major challenge for intrinsic models is the texture-copying artifact, which often happens on edges due to the entanglement of intrinsic components. The sparse WHDR metric in IIW dataset [23] and AP used in SAW dataset [24] are not able to reflect this artifact.

For edges, component entanglement often happens, when the model fails to determine whether the change is caused by reflectance or shading. Edges can result from the change of reflectance only, shading only or both. To evaluate the predictions, we need to have better understanding on what happens around these edges. In addition to edges with abrupt local changes, we’re also interested in how well the prediction fits the groundtruth around the relatively flat regions, e.g. in a constant-reflectance region, reflectance value shouldn’t change while shading values should fit tightly to the changes.

With the analysis above, we need to first design a data annotation scheme to annotate edges and regions of interest (Sec. 4.1). On top of the annotation, we design an diagnostic edge-aware metric to maximally reflect how model behaves (Sec. 4.2).

#### 4.1 Data Annotation Scheme

For CloIntrinsics testing set, we need data annotation on both edges \( E \) and regions \( R \) of interest. Considering the difficulty and accuracy during annotation, we propose to focus on annotating constant-reflectance regions and edges caused by reflectance only or shading only.

Specifically, region annotation \( R = \{ R_c \mid c = 1, 2, \cdots, C \} \) contains several regions \( R_c \) and elements in \( R_c \) have the same reflectance \( c \). The annotators are asked to find pixels with intrinsically the same “color”, i.e. the same reflectance, and annotate them with points or polygons. Instead of including comparison with inequal reflectance values, annotators can easily annotate more precise results.

For edges, component entanglement often happens, when the model fails to determine whether the change is caused by reflectance or shading. Edges can result from the change of reflectance only, shading only or both. To evaluate the predictions, we need to have better understanding on what happens around these edges. In addition to edges with abrupt local changes, we’re also interested in how well the prediction fits the groundtruth around the relatively flat regions, e.g. in a constant-reflectance region, reflectance value shouldn’t change while shading values should fit tightly to the changes.
The annotation collection pipeline includes data annotation and data verification, conducted by three annotators with background in intrinsic images. For data annotation, we ask two of the annotators to annotate the images twice. They are asked to only annotate the confident parts. The annotation will then be combined, and another inspector will verify the annotation. We noticed that it’s hard for the inspector to find mistakes directly by watching the edge annotation, but it’s easier for the inspector to judge whether reflectance and shading are well behaved. Based on this observation, we incorporate an interactive method \[9\] for annotation inspection. Specifically, we use our edge annotation as the prior to solve for intrinsic images, and the results will be displayed to the annotator. Only when our annotation leads to plausible decomposition results can we assume the annotation is reliable. With the above professional annotation procedure, we obtained high quality annotation on real-world images.

4.2 Metric Design

With region annotation \(\{R_c\}_{c=1,2,\cdots,C}\) and edge annotation \(\{E_R, E_S\}\), we define metric for region performance and edge performance separately.

**Region reflectance metric.** Pixels with the same reflectance should have similar values in the decomposition results. Given the predicted reflectance \(\hat{R}\), we calculate the variance within each annotated region as a metric to evaluate the performance of predicted reflectance. Specifically, for each region \(R_c\), we first normalize the mean to consider the ambiguity in scale,

\[
\hat{R}_{i,j} = \frac{|R_c|}{\sum_{(m,n) \in R_c} \hat{R}_{m,n}} \hat{R}_{i,j}.
\]

Then we compute the variance as the error measure of reflectance

\[
\text{RegionError}_R = \frac{1}{C} \sum_{c=1}^C \frac{1}{|R_c|} \sum_{(i,j) \in R_c} (\hat{R}_{i,j} - 1)^2.
\]

**Region shading metric.** Within each constant reflectance region \(R_c\), we can assume the reflectance is constant and compute the estimated groundtruth shading \(\hat{S}_c\), which is RGB image divided by reflectance. Given the predicted shading \(\hat{S}\), we compute scale-invariant mean square error (si-MSE) as a metric to evaluate global shading performance,

\[
si\text{-MSE}_R(\hat{X}, X) = \frac{1}{|R|} \sum_{(i,j) \in R} ||\alpha \hat{X}_{i,j} - X_{i,j}||^2,
\]

\[
\text{RegionError}_E = \frac{1}{C} \sum_{c=1}^C \text{si\text{-MSE}}_R(\hat{S}_c, S_c)
\]

\[
\sum_{c=1}^C \text{si\text{-MSE}}_R(0, S_c)
\]

where \(\alpha = \arg \min \sum_{(i,j) \in R} ||\alpha \hat{X}_{i,j} - X_{i,j}||^2\), and where we use a relative error similar to \[28\]. Considering that the estimated shading \(\hat{S}_c\) is not exactly the ground truth, we don’t accumulate the part of error when the prediction error is within the range of \(\pm 5\%\).

**Edge metric.** The most common artifact for edges is component entanglement. With edge annotation \(\{E_R, E_S\}\), we are able to evaluate model performance in an more interpretable way. Ideally, the predicted reflectance \(\hat{R}\) should change around \(E_R\) but not \(E_S\). Similarly, the predicted shading \(\hat{S}\) should change around \(E_S\) but not \(E_R\). We use local gradient magnitude to indicate the local changes, and assume it changes when local gradient magnitude is larger than a threshold \(\tau\). We first normalize in the same way as in Eq.\[1\] and get \(\hat{R}\) and \(\hat{S}\). Then, to indicate how well the predicted results agrees with the annotation, we define the accuracy of reflectance at \(E_S\) and the accuracy of shading at \(E_R\) as follows

\[
\text{Acc}_R^{(E_S)} = \frac{\sum_{(i,j) \in E_S} \mathbb{I}(||\nabla \hat{R}_{i,j}|| < \tau)}{|E_S|},
\]

\[
\text{Acc}_S^{(E_R)} = \frac{\sum_{(i,j) \in E_R} \mathbb{I}(||\nabla \hat{S}_{i,j}|| < \tau)}{|E_R|},
\]

where \(\mathbb{I}(\cdot)\) is the indicator function. The accuracies defined above directly indicate how reflectance and shading entangle with each other, making it interpretable and diagnostic. Similarly, we can also define the accuracy of reflectance at \(E_R\) as \(\text{Acc}_R^{(E_R)}\), and the accuracy of shading at \(E_S\) as \(\text{Acc}_S^{(E_S)}\),

\[
\text{Acc}_R^{(E_R)} = \frac{\sum_{(i,j) \in E_R} \mathbb{I}(||\nabla \hat{R}_{i,j}|| > \tau)}{|E_R|},
\]

\[
\text{Acc}_S^{(E_S)} = \frac{\sum_{(i,j) \in E_S} \mathbb{I}(||\nabla \hat{S}_{i,j}|| > \tau)}{|E_S|}.
\]

We finally use weighted harmonic mean as the metric for edge performance,

\[
F_R = \frac{w_1 + w_2}{\frac{w_1}{\text{Acc}_R^{(E_R)}} + \frac{w_2}{\text{Acc}_S^{(E_S)}}},
\]

\[
F_S = \frac{w_1 + w_2}{\frac{w_1}{\text{Acc}_R^{(E_R)}} + \frac{w_2}{\text{Acc}_S^{(E_S)}}},
\]

indicating edge performance of reflectance and shading respectively.

In summary, for the real-world testing set, we use \(\text{RegionError}_R\), \(\text{RegionError}_E\) to evaluate generally how well the predicted intrinsic images fit to the groundtruth. For common component entanglement artifacts, we use \(F_R\) and \(F_S\) to evaluate the edge performance of intrinsic models. By looking at \(\text{Acc}_R^{(E_S)}\), \(\text{Acc}_R^{(E_R)}\), \(\text{Acc}_S^{(E_R)}\), \(\text{Acc}_S^{(E_S)}\), we can learn diagnostic information on how model behaves around edges.

5 CLOTHINNET MODEL

The bottleneck for learning-based approaches with CNNs is the lack of effective data. Synthetic images lack the complexity of images in the wild and there’s nautrally a domain gap, while annotations on real world images are so sparse that it’s not adequate to learn a model in a purely data-driven manner. Existing datasets actually fail to provide the real world distribution of intrinsic images.

To address this problem, we propose Clothing Intrinsics Network (ClothInNet) model. As we can note, the domain gap of shading images between synthetic and real world is much larger than reflectance images, due to the complex shape and illumination conditions. We propose to acquire real world shading from single-color clothing images with minor additional annotation. With these data, we can jointly train a CNN with an adversarial learning module. By discriminating the output shading from real world shading, the
model learns to predict better shading results. Additionally, we introduce the gradient constraint loss as a prior for predicted reflectance and shading, to further improve the predictions.

5.1 Real World Shading from Single-color Clothing

As discussed above, real world shading data is vital but hard to densely annotate in pair. However, we can still make use of unpaired data.

As we can observe in fashion datasets like HumanParsing [45, 46], clothing can be roughly divided into two categories based on the differences in reflectance: single-color clothing and richly-textured clothing. As shown in Fig. 3, the clothing types, shape deformations and lighting conditions should be similar for the two categories. And from the physical meaning of reflectance and shading, we can assume the shading of single-color clothing and richly-textured clothing should have similar distribution. Intrinsic image decomposition for richly-textured clothing is quite hard, but it’s pretty easy to get the approximate shading of single-color clothing. This is because, single-color clothing has nearly constant reflectance and simply the grayscale image is a good approximation of shading. Single-color clothing takes a considerable part (around 20%) in fashion datasets, and there’re segmentation results of clothing items. We only need to annotate whether a clothing item is single-color, and we can collect a set of real world shading \( S_{\text{real}} \).

Specifically, we annotated HumanParsing [45, 46] dataset. We load the masked clothing items in the dataset and annotate whether it is single-color. This is only a single label so it’s pretty easy to annotate. And because we care more about the precision than recall of the annotation, we trained a simple CNN classifier to largely facilitate the annotation process. We got 20008 clothing items after area thresholding and filtering noisy items, and finally picked out 2602 single-color clothing items to form the shading set \( S_{\text{real}} \).

5.2 Model Architecture

ClothInNet contains a CNN generator and a CNN discriminator, as shown in Fig. 4. We train the model with CloIntrinsics \( \{I_{\text{synthetic}}, R_{\text{synthetic}}, S_{\text{synthetic}}\} \), a real world clothing image set \( \{I_{\text{real}}\} \), and the real world shading set \( \{S_{\text{real}}\} \) acquired in Sec. 5.1.

We use the synthetic dataset to produce dense supervision to the model, which helps it learn the basic principles of intrinsic images. The real world clothing image set \( \{I_{\text{real}}\} \) is to transfer the model to real world domain. The real world shading set \( \{S_{\text{real}}\} \) is used as positive sample to train an adversarial discriminator, and the CNN generator learns to fit to the real world distribution through adversarial training. Finally, the gradient constraint loss prevent reflectance and shading from changing simultaneously, which further constrain the texture-copying artifacts. We separately describe the supervision signals in the following part of this section.

Direct Supervision. Similar to previous models, the CNN generator consumes RGB images as input and predicts corresponding reflectance and shading images as outputs. When training with the synthetic dataset \( \{I_{\text{synthetic}}, R_{\text{synthetic}}, S_{\text{synthetic}}\} \), the model learns the general knowledge on intrinsic images from dense supervision. We use scale-invariant mean square error loss (si-MSE) as supervision signal, and enforce the predicted intrinsic images and its first order gradient to match with ground truth. The loss function can be written as follows

\[
L_R = \text{si-MSE}(\hat{R}, R) + \text{si-MSE}(\nabla \hat{R}, \nabla R),
\]

\[
L_S = \text{si-MSE}(\hat{S}, S) + \text{si-MSE}(\nabla \hat{S}, \nabla S).
\]

Additionally, we use reconstruction loss

\[
L_{\text{reconstruct}} = \frac{1}{N} \sum_{i=1}^{N} (I_i - R_i \odot S_i)^2
\]

to encourage Hadamard product relationship \( I = R \odot S \).

The direct supervision through synthetic dataset can form a multi-task loss

\[
L_{\text{direct}} = \lambda_R L_R + \lambda_S L_S + L_{\text{reconstruct}}
\]

where \( \lambda_R, \lambda_S \) weigh different terms.

Adversarial Supervision. When training with real world images \( I_{\text{real}} \), there’s no paired groundtruth. But we can
train a discriminator and learn from $\mathcal{S}_{\text{real}}$ in an adversarial manner.

The discriminator $D$ takes shading images $S$ as input and predicts a binary label indicating whether it’s a real shading image. The positive samples come from the real world shading set $\{\mathcal{S}_{\text{real}}\}$ acquired in Sec. 5.1. The negative samples includes the shading images predicted by the CNN generator and the grayscale image of richly-textured clothing. The loss function to train the discriminator is

$$L_D = \text{BCE}(D(S), 1) \left( S \in \mathcal{S}_{\text{real}} \right)$$

where BCE is binary cross entropy loss

$$\text{BCE}(\hat{y}, y) = y \log \hat{y} + (1 - y) \log(1 - \hat{y}),$$

and $\mathbb{1}(\cdot)$ is the indicator function.

To train the CNN generator to predict realistic shading that fools the discriminator, for the shading prediction $\hat{S}$, we define the adversarial loss

$$L_{ad} = \text{BCE}(D(\hat{S}), 1)$$

as additional supervision for CNN generator. From a probabilistic view, we know $p(S|I) \propto p(I|S)p(S)$. The shading distribution $p(S)$ provided by $\mathcal{S}_{\text{real}}$ is helpful for training models when there’s no available pairwise dense annotation.

**Exclusive Gradient Constraint.** Large discontinuities seldom occur at the same time in reflectance and shading. As the adversarial supervision already improves the shading performance, we introduce a novel loss term

$$L_{grad} = \frac{1}{N} \sum_{i=1}^{N} \| \nabla \hat{R}_i \cdot \nabla \hat{S}_i \|^2$$

to further constrain the edge behaviour and improve the performance of reflectance. When shading is changing, the loss $L_{grad}$ penalize the local changes of reflectance or at least in the different direction from $\nabla \hat{S}$. This simple loss term enforce explicit reasoning around edges, and brings amazing improvements on reflectance.

To sum up, we train our ClothInNet model with $L_D$ in Eq. 15 for CNN discriminator and

$$L_G = L_{direct} + \lambda_{ad} L_{ad} + \lambda_{grad} L_{grad}$$

for CNN generator, where $\lambda_{ad}$, $\lambda_{grad}$ weigh the loss terms.

### 6 Experiments

In this section, we perform extensive evaluation on our methods, including qualitative results on real world clothing images and quantitative comparison with state-of-the-art methods. We quantitatively evaluate the methods on CloIntrinsics testing set and provide additional cross-domain evaluation on MIT Intrinsic Images Dataset [28]. We first introduce detail settings in Sec. 6.1. Then we compare qualitatively and quantitatively in Sec. 6.2 and Sec. 6.3. We further show some graphics applications in Sec. 6.4.
Fig. 5. Qualitative comparisons on real world clothing images. For each method, the left result is reflectance and the right is shading. Our model significantly removes texture-copying artifacts while retaining tiny details. Best viewed zooming in.

TABLE 1
Quantitative evaluation on CloIntrinsics testing set.

| Model            | $\text{Acc}_{\text{R}}^{(E)}$ | $\text{Acc}_{\text{S}}^{(E)}$ | $\text{Acc}_{\text{R}}^{(S)}$ | $\text{Acc}_{\text{S}}^{(E)}$ | $F_{\text{R}}$ | $F_{\text{S}}$ | RegionError$_{\text{R}}$ | RegionError$_{\text{S}}$ |
|------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|----------------|----------------|--------------------------|--------------------------|
| Retinex [47]     | 0.3890                        | 0.9209                        | 0.4488                        | 0.9346                        | 0.4546        | 0.5158        | 0.0383                   | 0.0152                   |
| Zhao et al. [12] | 0.5373                        | 0.8874                        | 0.3366                        | 0.9915                        | 0.5961        | 0.4032        | 0.0434                   | 0.0129                   |
| BigTime [26]     | 0.5646                        | 0.9952                        | 0.5633                        | 0.9968                        | 0.6331        | 0.6320        | 0.0039                   | 0.0115                   |
| CGIntrinsics [20]| 0.4450                        | 0.9945                        | 0.7392                        | 0.9317                        | 0.5163        | 0.7794        | 0.0159                   | 0.0193                   |
| UNet-CLO         | 0.5643                        | 0.9846                        | 0.4570                        | 0.8705                        | 0.6317        | 0.5185        | 0.0171                   | 0.0084                   |
| + Ad Supervision | 0.6081                        | 0.9962                        | 0.7962                        | 0.9373                        | 0.6737        | 0.8273        | 0.0169                   | 0.0089                   |
| + Grad Constraint| 0.7780                        | 0.9943                        | 0.8172                        | 0.9447                        | 0.8227        | 0.8457        | 0.0055                   | 0.0076                   |

TABLE 2
Quantitative cross-domain evaluation on MIT dataset.

| Model            | LMSE - R | LMSE - S |
|------------------|----------|----------|
| Retinex [47]     | 0.0366   | 0.0419   |
| Zhao et al. [12] | 0.0311   | 0.0267   |
| BigTime [26]     | 0.0341   | 0.0253   |
| CGIntrinsics [20]| 0.0349   | 0.0259   |
| ClothlnNet       | 0.0357   | 0.0229   |

Please note CloIntrinsics testing set contains real-world images and is independent from CloIntrinsics training set, so the comparison is fair. We use $F_{\text{R}}$, $F_{\text{S}}$ as the measure of edge performance and RegionError$_{\text{R}}$, RegionError$_{\text{S}}$, as metrics for general global performance. $\text{Acc}_{\text{R}}^{(E)}$, $\text{Acc}_{\text{R}}^{(S)}$, $\text{Acc}_{\text{S}}^{(E)}$, $\text{Acc}_{\text{S}}^{(S)}$ can give interpretable information on how model performs around the edges. The results are shown in Table 1.

Our proposed metrics give novel insights on how model performs around edges and regions of interest. All baseline methods perform well on $\text{Acc}_{\text{R}}^{(E)}$ and $\text{Acc}_{\text{S}}^{(E)}$, but have rather low scores on $\text{Acc}_{\text{R}}^{(S)}$ and $\text{Acc}_{\text{S}}^{(S)}$. This indicates that the models learn to recall the local changes in the prediction but is careless in the precision. This leads to severe texture-copying artifacts. Our ClothlnNet model significantly improves the quantitative performance and we show the ablation study in Table 1. We start with a UNet model trained on CloIntrinsics with direct supervision, which we refer to as UNet-CLO. Then we add our proposed adversarial module and gradient constraint loss on top. As we see, the adversarial module significantly im-
proves the shading edge performance $F_S$. This is largely due to the significant improvement on $\text{Acc}_S^{(E_S)}$, indicating that the predicted shading images refrain from changing at edges caused mainly by reflectance ($E_S$). This is consistent with the qualitative analysis. Such manner for shading images is quite beneficial. With gradient constraint loss on top, the model shows comprehensive improvement, especially for reflectance. This agrees with our expectation. When shading is changing abruptly, reflectance is largely penalized and thus improve the $\text{Acc}_S^{(E_S)}$. When shading is smoothly changing, it also slightly penalize reflectance changes and thus improve $\text{RegionError}_S$. Comparing the results of CGIntrinsics and UNet-CLO, we can see that models trained with CloIntrinsics have much smaller shading region errors. This indicates models trained with CloIntrinsics generally fits tighter to the groundtruth, preserving more detailed information in shading. This validates the effectiveness of in-domain knowledge provided by diverse shapes and textures in CloIntrinsics training set.

We also show cross-domain evaluation on MIT dataset in Table 2. Although the model is working on clothing domain, it still generalize well to MIT dataset. Our model predicts comparable reflectance and better shading compared to models trained with CGIntrinsics and BigTime.

**Discussion.** Our proposed diagnostic metrics provide more interpretable information on how model behaves, thus providing novel insights on this task. The ill-posed nature of intrinsic image decomposition requires algorithms to disentangle local changes into different components. However, the commonly employed regression and reconstruction loss tend to recall more local changes and produce predictions with low precision. To address this, we propose to use adversarial learning and a gradient exclusive loss to enforce both implicit and explicit reasoning on local changes. Similar adversarial module was employed in previous work [35], but we also stress the different insight for using such a module and the non-trivial effort on selecting effective data, i.e. the real-world shading set. The novel gradient constraint loss explicitly penalizes local entanglement and thus performs well on challenging clothing images.

### 6.4 Applications

With our intrinsic decomposition results of clothing images, we can perform graphics applications leveraging the embedded geometry information in the decomposed shading image and the color information in the reflectance image. **Color style editing.** We fix the shading image and perform color style editing on the reflectance, as shown in Fig. 6. The image editing results show that the wrinkle and shape details are preserved.

**Relighting.** We iteratively optimize spherical harmonic lighting and normal map, following [52]. The relighting result is shown in Fig. 7.

### 7 Conclusion

In this paper, we extensively studied the task of intrinsic image decomposition for clothing images. We proposed a clothing intrinsic images dataset, an interpretable diagnostic evaluation metric, and a simple but effective model. The proposed adversarial method and carefully designed loss terms significantly reduces texture-copying artifacts, outperforming existing state-of-the-art approaches. The methods proposed in this paper are also able to extend to other domain, highlighting its value for intrinsic image decomposition research.

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