TransCC: Transformer-based Multiple Illuminant Color Constancy Using Multitask Learning

Shuwei Li¹, Jikai Wang, Michael S. Brown², Robby T. Tan¹,³
¹ National University of Singapore, ² York University, ³ Yale-NUS College
shuwei@u.nus.edu, jkwang992@gmail.com, mbrown@eecs.yorku.ca, robbytan@nus.edu.sg

Abstract

Multi-illuminant color constancy is a challenging problem with only a few existing methods. For example, one prior work used a small set of predefined white balance settings and spatially blended among them, limiting the solution to predefined illuminations. Another method proposed a generative adversarial network and an angular loss, yet the performance is suboptimal due to the lack of regularization for multi-illumination colors. This paper introduces a transformer-based multi-task learning method to estimate single and multiple light colors from a single input image. To help our deep learning model have better cues of the light colors, achromatic-pixel detection, and edge detection are used as auxiliary tasks in our multi-task learning setting. By exploiting extracted content features from the input image as tokens, illuminant color correlations between pixels are learned by leveraging contextual information in our transformer. Our transformer approach is further assisted via a contrastive loss defined between the input, output, and ground truth. We demonstrate that our proposed model achieves 40.7% improvement compared to a state-of-the-art multi-illuminant color constancy method on a multi-illuminant dataset (LSMI). Moreover, our model maintains a robust performance on the single illuminant dataset (NUS-8) and provides 22.3% improvement on the state-of-the-art single color constancy method.

1. Introduction

Computational color constancy determines the dominant color cast caused by the scene’s dominant illumination in a sensor image. Once the sensor’s response to the color cast has been estimated, the image can be corrected via a white-balance procedure. Computational color constancy is one of the key operations applied by cameras and is critical to obtaining an accurate image. A number of color constancy methods have been proposed using various strategies, e.g., low-level statistical methods, gamut-based methods, and learning-based methods. Recently, deep learning has become a mainstream approach due to its impressive performance [1, 12, 38, 49]. However, most color constancy methods, including state-of-the-art deep learning methods, assume the scene is illuminated by a single uniform light source. In many real-world situations, particularly in indoor settings, the assumption is not valid, as multiple illuminations are commonly present. When multi-illuminations are present, the correction of only one illuminant leaves strong color casts in the image, as shown in Figure 1.

There has been significantly less work targeting scenes with multiple illuminations. Early work [26] applied statistical-based illumination estimation locally to image
patches. Similarly, [32] used a nearest-neighbor approach that compared the statistics of pixels to those in a training set. These earlier methods worked only for selected images and highlighted the difficulty of the multi-illumination problem.

Work by [44] introduced a GAN-based approach incorporating discriminator loss and a conventional color constancy loss. Adding the GAN loss improved performance, but the method often leaves noticeable spatial artifacts in the corrected image. Recent work by [4] provided a solution that rendered the captured scene to a small set of predefined white-balance settings. The work estimated how to blend between this set of white-balanced results. The reliance on a small predefined set of solutions hindered the method’s practicality in handling general light colors.

In this paper, we address the multi-illumination problem using a transformer-based approach. The main benefit of transformers [27, 47] is the implicit incorporation of attention to the local features and their long-range dependencies to other parts of the image. We introduce a novel surface color representation learning scheme to improve our transformer features by exploiting contrastive learning. By this contrastive loss, the color features on different surfaces are required to be disentangled while maintaining the same before and after processing in the same location. Finally, we design a multi-task learning framework by exploiting two auxiliary tasks: (1) achromatic-pixel detection and (2) edge detection. Achromatic-pixel detection helps the main color constancy module focus on local achromatic regions that strongly indicate local light colors, while edge detection can indicate apparent color discontinuities related to surface colors and illumination colors [20, 46].

In summary, our contributions are as follows:

- We introduce a transformer-based generator method to address the problem of multi-illuminant color constancy, where the transformer model captures long-range dependencies from different regions in the input image to provide more contextual information about the scene.

- We propose a novel surface color representation scheme using contrastive learning, which helps our extracted features to be more invariant to different illuminations.

- Finally, we show the incorporation of a multi-task learning procedure improves the performance of our model. The two auxiliary tasks provide extra regularization by requiring the shared encoder to extract related features.

Our proposed model achieves 40.7% improvement compared to a state-of-the-art multi-illuminant color constancy method on a multi-illuminant dataset (LSMI). In addition, our model maintains a robust performance on the single illuminant dataset (NUS-8) and provides 22.3% improvement on the state-of-the-art single color constancy method.

2. Related Work

Color Constancy  Color constancy – also referred to as white-balancing – is the process of removing color casts caused by the scene illumination. The fundamental challenge for color constancy is to estimate the illumination for the image. The problem can be divided into two scenarios: (1) uniform color constancy, which assumes that there exists only one uniform illumination color in the scene; and (2) multi-illuminant color constancy, assuming more than one illumination color in the scene.

As discussed in Section 1, the vast majority of methods focus on uniform color constancy. Multi-illuminant color constancy is significantly more challenging because it is necessary to estimate spatially varying illumination color over the image, instead of a single RGB color needed for uniform illumination. Early works (e.g., [15, 16, 26]) address both problems using statistic-based features derived from empirical priors. While these methods required no training data, they had limited ability to handle scenes with multiple illuminations.

Statistic-based methods have been replaced by data-driven approaches using either conventional machine learning, or more recently, neural networks. For example, for uniform color constancy, many CNN-based solutions have been proposed (e.g., [12, 28, 53]). The current state-of-the-art method CLCC by Lo et al. [38] introduces contrastive learning to the uniform color constancy.

For the multi-illuminant color constancy, the lack of large-scale datasets leads to the few methods in the learning-based approach. For example, Joze et al. propose a K-NN method [32] that corrects spatial regions based on super pixels. Afifi et al. [4] proposed a method that avoids illumination estimation. Instead, an image is corrected with a predefined set of illuminations. A CNN is used to estimate per-pixel blending weights among the images. This approach works well, but only for scenes within the predefined set of illuminations. More relevant to our work is that by Sidorov [44] who propose AngularGAN, a generative adversarial network (GAN) method trained on a synthetic dataset. This method is considered to be the current state-of-the-art method for multi-illuminant color constancy. AngularGAN produces good results but often leaves noticeable artifacts through the image.

Vision Transformer  A transformer is a neural network structure based on a self-attention mechanism. Transformers can be considered an alternative strategy to convolutional neural networks. Work by [22] shows that a transformer-based architecture was highly effective for
3. Proposed Method

Given an input image taken in a single or multiple illuminant color environment, our goal is to restore its white-balanced counterpart as if the scene is lit by a uniform achromatic light source. The corresponding pixel-level illuminant color map can be calculated from our output image (i.e., the white-balanced image), and used for error calculation. While our focus is on multiple illuminant colors, our network also works for a single illuminant color, if it is trained on a single light color dataset.

As shown in Fig. 2, our network exploits multi-task learning, where color constancy is the primary task, and achromatic pixel detection and edge detection as auxiliary tasks. The auxiliary tasks are trained jointly with the primary task and act as regularization. In our U-shaped architecture, there are three branches after the shared encoder. Each branch has its own decoder to perform specific predictions. In the training stage, the ground truths of white-balanced images also serve as the ground truths of the achromatic-pixel detection. Edge detection is trained on pseudo labels which are generated by the pretrained HED model [50].

Specifically for the primary color constancy task, a patch-wise contrastive learning scheme is exploited as important regularization. To improve the color constancy performance, a patch similarity loss is calculated between the generated images and ground truths. With our similarity loss, the spatial smoothness of the predictions and ground truths is made consistent. Note that, the auxiliary tasks, surface similarity loss, and contrastive learning are required only in the training process.

3.1. Multi-task Learning Structure

Color constancy is an ill-posed problem. There are two unknowns on each pixel: illuminant color and surface color. Moreover, in multi-illuminant settings, since the illuminant colors can be different for different pixels, learning the mapping between the input image and output white-balanced image can be challenging, particularly when the datasets of this task are usually small. Multi-task learning can improve the generalization of the model by obtaining knowledge in related tasks that can serve as extra regularization [54]. In our case, we design two tasks that can interact with the desired features of the primary task in a more direct manner.

Achromatic Pixel Detection

Achromatic (also called neutral) pixels refer to the object surfaces that have no colors, such as white, gray, or black surfaces. Detecting achro-
matic surfaces is an important process in some color constancy methods [12, 41]. By knowing which surfaces are achromatic, a model can estimate the local illuminant colors based on the input image colors corresponding to the achromatic surfaces directly.

In the training process, given the ground truth image \( x \) of the primary color constancy task, the auxiliary achromatic detection model is required to predict a weight map, \( w \), where \( w_{ij} \in [0, 1] \) from the input image \( I \) (indexes \( i, j \) indicate the pixel location). The chromaticity of the weighted average of the ground truth image can be calculated as:

\[
c = \frac{\sum_{i=1}^{H} \sum_{j=1}^{W} x_{ij} w_{ij}}{Z},
\]

where \( Z \) is a normalization factor to make \( c \) have unit Euclidean norm. The achromatic loss [12] can then be expressed as:

\[
L_A(c) = 1 - \frac{c_r + c_g + c_b}{\sigma + \sqrt{3(c_r^2 + c_g^2 + c_b^2)}},
\]

where \( \sigma = 10^{-4} \) is a small number to stabilize the ratio. This loss encourages the weight map to give a higher weight to the achromatic pixels. The loss only decreases to near zero when the three elements in \( c \) are close to each other, which represents an achromatic pixel.

**Edge Detection** Edge detection is a task to predict color and texture boundaries in images. In statistic-based color constancy methods (e.g., [11, 14, 18, 46]), spatial-statistical methods use gradients and frequency information to provide relatively large intensity differences, which are the key to illumination estimation. In many learning-based methods, the models extract the features of scene contents, including the surface texture and color discontinuities. For this reason, we consider the edge detection task as an auxiliary task that can help our model to learn the cues of surface and light colors.

In the training process, since there are no edge detection ground truths for color constancy datasets, our edge detection model is supervised by pseudo labels. In our experiment, the pseudo labels are generated by a pretrained HED model [50]. In brief, this method learns rich hierarchical representations by convolutional neural networks and performs fast edge and object boundary detection. A mean square error (MSE) loss \( L_E \) is implemented to compare the prediction of our model and the pseudo label.

**U-shaped Structure** In most existing deep learning color constancy methods (e.g., [4, 13, 38, 44]), CNNs are adopted in the encoder and decoder with residual blocks to merge the contextual features. To overcome the intrinsic receptive-field limit of CNNs [30, 36], we proposed to utilize a transformer-based U-shaped architecture. Our network is built upon the transformer and UNet [42], which has a U shape and skip-connections. For each task, the network consists of an encoder, middle blocks (for the primary task), and a decoder. The encoder is shared by three tasks, while each task has its own decoder.

Our encoder attempts to extract features of local illuminant and surface colors, as well as the cues for the auxiliary tasks. To allow potential long-range interactions of features in our network, a Transformer-based [48] middle block is inserted between the encoder and decoder. As Fig. 2 shows, the middle block consists of two ResNet blocks, a normalization layer, a convolutional projection layer, and a multi-head attention layer. This Transformer-based block can introduce dynamic attention and global context fusion into our model [48].

3.2. Contrastive Learning

In our primary color constancy task, our network extracts features of the surface colors and outputs a white-balanced image. This output requires the feature representations of the surface colors. Since the surface colors are invariant to light colors, so do their feature representations. For this reason, we apply a contrastive loss to the features of the input, output, and ground truth.

Contrastive learning improves representation learning by
pulling positive samples to the anchor sample while separating negative samples and the anchor sample in the representation space. As shown in Fig. 3, instead of using image patches, we use the features in the middle blocks of the primary color constancy task to conduct patch-wise contrastive learning.

The middle blocks’ features of the input image, output image, and ground truth are fed into a 2-layer MLP projection block, denoted as $z_i, z_o, z_g$, respectively. The anchor sample $v^*$ is a vector randomly selected on the feature map $z_o$. The positive samples $v^+$ are the two vectors on the feature maps $z_1$ and $z_g$ of the same location. The negative samples $v^-$ are $N$ vectors randomly selected on the feature maps $z_i$ and $z_g$ of different locations. The decoupled information (DCE) loss [52] is employed as a contrastive loss, which is based on the cross-entropy loss and calculates the cosine similarity of the samples. The contrastive loss can then be formulated as:

$$L_{\text{contrastive}} = -\log \left( \frac{\sum_{i=1}^{N} \exp(v \cdot v_i^+ / \tau)}{\sum_{i=1}^{N} \exp(v \cdot v_i^- / \tau)} \right),$$

where $N$ is the number of negative samples and $\tau$ is a scaling factor of temperature. There are two positive pairs and $N$ negative pairs for contrastive loss calculation, therefore the loss can be considered as the cross entropy loss of $(N+2)$-way classification.

A previous method [38] implements data augmentation on the input images and performs a contrastive loss for learning the representations of a single uniform illuminant color. In contrast, our method conducts a patch-wise contrastive loss in learning surface color representations, which consequently enables us to handle both the single and multiple illuminant color settings.

### 3.3. Patch Similarity Loss

Conventional losses (e.g., $L1$ loss, Mean Angular Error (MAE) loss) generate the error on the corresponding pairs of pixels, which has a weak constraint on the inconsistency problem. For instance, colorful textures should not be predicted on a gray wall, which can happen in image translation-based methods. Moreover, the correlation among pixels should also be consistent between the predictions and ground truths. Such correlation reflects the spatial smoothness of the surface colors. For this reason, we propose a patch-based surface similarity loss, which is calculated between the ground truth and our predicted surface color image.

We randomly select a patch of size $k \times k$ on the predicted surface image $x$, then set the center as the anchor pixel $x_{\text{anchor}}$. The similarity map $S_{\text{surf}}$ is then defined as:

$$S_{\text{surf}}^{(ij)} = \arccos \frac{x_{ij} \cdot x_{\text{anchor}}}{\|x_{ij}\| \|x_{\text{anchor}}\|},$$

by which the angle of color between the anchor pixel $x_{\text{anchor}}$ and other pixels $x_{ij}$ in the patch are calculated. With the same process, the similarity map $\hat{S}_{\text{surf}}$ of the same patch on the ground truth can be calculated. Hence, the patch similarity loss between the two similarity maps can be expressed as:

$$L_{\text{surf-sim}} = \| S_{\text{surf}} - \hat{S}_{\text{surf}} \|.$$  

Note that the patch similarity loss is an extra constraint to make the predictions follow the smoothness of the ground truths, and should not be considered as a smoothing operation. In practice, we randomly select $n$ patches for each image.

### 4. Experiments

#### 4.1. Implementation Details

**Network Details** In our implementation, the shared encoder consists of 4 encoder blocks while each decoder has 4 decoder blocks. One transformer-based middle block is implemented between the encoder and decoder in our primary color constancy task. In our contrastive learning implementation, 16 negative samples are randomly sampled on each image. The 2-layer MLP has a $512 \times 512$ structure. As for surface similarity loss, we randomly select $n = 2$ patches during the similarity loss calculation. Each patch has a size of $1/16$ of the output image.

**Training Setting** The experiments are conducted on a 24GB RTX 3090 GPU. The training images are resized to the size of $256 \times 256$, while the same resolution is set for the generated images. The batch size is set as 1. The training of our model uses the Adam [34] optimizer for 200 epochs using a step decay learning rate scheduler. The initial learning rate is 0.001 and it decays to 0 after 100 epochs. The loss weights are all set as 1 except $\lambda_1 = 0.1$. 

**Total Loss** Besides the mentioned losses, the $L1$ loss and the mean angular error (MAE) loss [44] are also used. To calculate MAE, in brief, the estimated illuminant map is firstly obtained by dividing the input image by the output image on the pixel level. Similarly, the ground truth illuminant map is obtained by dividing the input image by the ground truth image. MAE is the mean of the pixel-wise angular difference between the two maps.

Our total loss is represented as:

$$L_{\text{total}} = \lambda_1 L_{\text{A}} + \lambda_2 L_{\text{E}} + \lambda_3 L_{\text{L}} + \lambda_4 L_{\text{MAE}} + \lambda_5 L_{\text{surf-sim}} + \lambda_6 L_{\text{contrastive}},$$

where $\lambda$’s are the weights of different loss components. $L_1$ is the mean average error loss between the ground truths and predicted images.
4.2. Dataset and Evaluation Metrics

We use three color constancy datasets to evaluate our method’s performance for multi-illuminant and single-illuminant environments. To evaluate our method with multiple illumination colors, we use Large Scale Multi-Illuminant (LSMI) Dataset [33]. Our evaluation on single-illuminant environments follows CLCC [38] and AWB [4], which use the NUS-8 dataset [20] and CUBE+ dataset [7], respectively. During our experiments, we masked all the Macbeth Color Checkers (MCC) by setting the pixel values as (0,0,0) in RGB space. For training stability, $L_1$, $L_{surf-sim}$, and $L_{MAE}$ loss in our method are not calculated in these regions.

**LSMI Dataset [33]** The large scale multi-illuminant (LSMI) dataset contains 7,486 images captured by 3 different cameras on more than 2,700 scenes. In each scene, there are 1-3 light sources, including natural and man-made light sources. We use the whole dataset and split it to train, validation, and test sets with the ratio of 0.7,0.2, and 0.1.

**NUS-8 Dataset [20]** The NUS-8 dataset is widely used in single-illuminant color constancy studies. It has 1,736 lin-
Table 1. Comparison on the Cube+ dataset [7]. We report mean, first, second (median), and third quantile (Q1, Q2, and Q3) of mean angular error (MAE) and ΔE 2000.

| Method                  | MAE Mean | Q1 | Q2 | Q3 | ΔE2000 Mean | Q1 | Q2 | Q3 |
|-------------------------|----------|----|----|----|-------------|----|----|----|
| FC4 [28]                | 6.49     | 3.34 | 5.99 | 8.59 | 10.38       | 6.6 | 9.76 | 13.26 |
| Quasi-U [12]            | 6.12     | 4.95 | 8.88 | 13.73 | 20.25       | 5.21 | 10.37 |
| Interactive WB [3]      | 4.64     | 2.12 | 3.64 | 5.98 | 6.29        | 3.28 | 5.17 | 7.45 |
| KNN WB [5]              | 4.12     | 1.96 | 3.17 | 5.04 | 5.68        | 3.22 | 4.61 | 6.70 |
| AWB [4] $p = 64$, WB = {t,f,d,c,s} | 4.05 | 1.40 | 2.12 | 4.88 | 4.89       | 2.16 | 3.10 | 6.78 |
| Deep WB [2]             | 3.45     | 1.87 | 2.82 | 4.26 | 4.59        | 2.08 | 3.81 | 5.53 |
| TransCC                 | 2.71     | 1.05 | 1.59 | 3.21 | 3.31 | 2.45 | 2.87 | 3.42 |

Table 2. Angular error of various methods on the NUS-8 dataset. By averaging predicted illuminant colors as the final prediction, TransCC achieves the best results on the mean, median, tri-mean, and worst-25%.

| Method                  | Mean | Median | Tri. | Best25% | Worst25% |
|-------------------------|------|--------|------|---------|---------|
| White-Patch [15]        | 10.62 | 10.58  | 10.49 | 1.86    | 19.45   |
| Edge-based Gamut [8]    | 8.43  | 7.05   | 7.37  | 2.41    | 16.08   |
| Pixel-based Gamut [8]   | 7.70  | 6.71   | 6.90  | 2.51    | 14.05   |
| Intersection-based Gamut [8] | 7.20 | 5.97   | 6.28  | 2.20    | 14.61   |
| Gray-World [16]         | 4.14  | 3.20   | 3.39  | 0.90    | 9.00    |
| Bayesian [25]           | 3.67  | 2.73   | 2.91  | 0.82    | 8.21    |
| NIS [19]                | 3.71  | 2.60   | 2.84  | 0.79    | 8.47    |
| Shades of Gray [24]     | 3.40  | 2.57   | 2.73  | 0.77    | 7.41    |
| 1st-order Gray-Edge [46] | 3.20  | 2.22   | 2.43  | 0.72    | 7.36    |
| 2nd-order Gray-Edge [46] | 3.20  | 2.26   | 2.44  | 0.75    | 7.27    |
| Spatio-spectral (GenPrior) [19] | 2.96 | 2.33   | 2.47  | 0.80    | 6.18    |
| Corrected-Moment (Edge) [23] | 3.03 | 2.11   | 2.25  | 0.68    | 7.08    |
| Corrected-Moment (Color) [23] | 3.05 | 1.90   | 2.13  | 0.65    | 7.41    |
| Cheng et al. [20]       | 2.92  | 2.04   | 2.24  | 0.62    | 6.61    |
| CCC (dist+ext) [9]      | 2.38  | 1.48   | 1.69  | 0.45    | 5.85    |
| Regression TreeTree [21] | 2.36  | 1.59   | 1.74  | 0.49    | 5.54    |
| DS-Net (HypNet + SelNet) [43] | 2.24 | 1.46   | 1.68  | 0.48    | 6.08    |
| FFCC-4 channels [10]    | 1.99  | 1.31   | 1.43  | 0.35    | 4.75    |

Table 3. Mean value of the scores in the user study comparison. 16 groups of images are selected in the LSMI dataset [33] with 8 of them in single illuminant color and 8 of them in multiple illuminant colors. The scoring range is 1-10.

| Aspects                      | Ours | Ang.GAN [44] | AWB [4] | Patch CNN [13] |
|------------------------------|------|--------------|--------|----------------|
| White Balancing              | 8.7  | 7.6          | 6.3    | 5.9            |
| Image Quality                | 9.1  | 5.7          | 8.1    | 4.2            |

CNN [13], AWB [4], and AngularGAN [44] on the LSMI [33] dataset. As shown in Fig. 4, our method generates color-corrected images with higher quality, while the state-of-the-art methods fail to handle complex illuminants. Particularly, our method has a better capability to capture illuminant information under multiple light colors.
Table 4. Comparison of overall mean angular error on the LSMI dataset [33]. TransCC achieves the best result among all the methods.

| Method               | Mean  | Median |
|----------------------|-------|--------|
| Gray-World [16]      | 11.3  | 8.8    |
| White-Patch [35]     | 12.8  | 14.3   |
| 1st-order Gray-Edge [46] | 12.1  | 10.8   |
| PCA [20]             | 10.9  | 10.7   |
| Gray Pixel(std) [40] | 16.8  | 17.0   |
| Gijsenij et al. [26] | 18.0  | 17.0   |
| GP(M=2) [40]         | 17.1  | 17.4   |
| Hussain WP [31]      | 17.7  | 16.9   |
| N-WB (GW) [6]        | 13.9  | 13.1   |
| N-WB (WP) [6]        | 9.6   | 8.8    |
| N-WB (GE1) [6]       | 12.1  | 10.8   |
| N-WB (PCA) [6]       | 8.3   | 7.4    |
| N-WB (GP(std)) [6]   | 12.4  | 11.2   |
| AWB [5]              | 9.54  | 8.19   |
| Patch CNN [13]       | 4.82  | 4.24   |
| AngularGAN [44]      | 4.69  | 3.88   |
| TransCC              | 2.78  | 2.15   |

Table 5. Comparison of mean angular error under different number of light colors on the LSMI dataset [33].

| Method | Mean | Median |
|--------|------|--------|
| Single | 2.60 | 1.95   |
| Multi  | 2.85 | 2.28   |

Table 6. Ablation studies conducted on the LSMI dataset [33]. The proposed components are added into the framework progressively and show positive effects.

| Aux. | Aux. | Surf-S. | Cont. | Mean | Median |
|------|------|---------|-------|------|--------|
|      |      |         | Loss  |      |        |
| APD  | ED   | Loss    | Loss  |      |        |
| ✓    | ✓    | ✓       | ✓     | 3.42 | 3.00   |
| ✓    | ✓    | ✓       | ✓     | 2.92 | 2.30   |
| ✓    | ✓    | ✓       | ✓     | 2.88 | 2.33   |
| ✓    | ✓    |        | ✓     | 2.84 | 2.10   |
| ✓    | ✓    |        | ✓     | 2.78 | 2.15   |

Figure 5. As the illumination changes, the feature maps with $L_{contrastive}$ remain unchanged, while those without $L_{contrastive}$ change significantly.

**Quantitative Evaluation** We evaluate our method with the mean angular error and also assess it based on its performance under different numbers of light colors. As shown in Table 4, our method outperforms the current state-of-the-art methods in every metric. To be specific, our method has 40.7% less mean of the MAE compared to AngularGAN [44].

It is worth noting that our method shows a robust performance regardless of how many light colors exist in the scene. As shown in Table 5, our method has a closed MAE when facing a multiple number of illuminant colors.

**4.5. Ablation Studies**

We compare the quantitative performance of models trained on different settings on the LSMI dataset [33]. The experiments start by removing all the components except our backbone. Then, we progressively add components of our proposed method into it. In Fig. 5, we also compare the feature maps in different illuminations with and without our contrastive loss to show its effect.

By individually using Achromatic Pixel Detection (APD) and Edge Detection (ED) as auxiliary tasks, their positive effects of them are shown. When each component is added to the framework, an improvement can be observed. It shows the best performance when all the proposed components are added. The ablation studies show that all the components in our proposed method are important.

**5. Conclusion**

We have presented a novel transformer-based, multi-task learning network to address the multi-illuminant color constancy problem. Our method introduced several important constraints for this considerably ill-posed problem. Specifically, a multi-task learning framework uses auxiliary tasks related to color constancy, which serves as an extra regularization. In addition, our surface similarity loss provides the constraint on the smoothness of the surface color. Finally, a contrastive learning scheme is performed between the input, output, and ground truth images. The contrastive learning scheme helps constrain the model in the feature space. Our experiments show that our proposed components work together to achieve state-of-the-art performance for both single and multiple illumination corrections.
References

[1] Mahmoud Afifi, Jonathan T Barron, Chloe LeGendre, Yun-Ta Tsai, and Francois Bleibel. Cross-camera convolutional color constancy. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 1981–1990, 2021.

[2] Mahmoud Afifi and Michael S Brown. Deep white-balance editing. In Proceedings of the IEEE/CVF Conference on computer vision and pattern recognition, pages 1397–1406, 2020.

[3] Mahmoud Afifi and Michael S Brown. Interactive white balancing for camera-rendered images. In Color and Imaging Conference, volume 2020, pages 136–141. Society for Imaging Science and Technology, 2020.

[4] Mahmoud Afifi, Marcus A Brubaker, and Michael S Brown. Auto white-balance correction for mixed-illuminant scenes. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 1210–1219, 2022.

[5] Mahmoud Afifi, Brian Price, Scott Cohen, and Michael S Brown. When color constancy goes wrong: Correcting improperly white-balanced images. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 1535–1544, 2019.

[6] Teruaki Akazawa, Yuma Kinoshita, Sayaka Shiota, and Hitoshi Kiya. N-white balancing: White balancing for multiple illuminants including non-uniform illumination. IEEE Access, 10:89051–89062, 2022.

[7] Nikola Banić, Karlo Koščević, and Sven Lončarić. Unsupervised learning for color constancy. arXiv preprint arXiv:1712.00436, 2017.

[8] Kobus Barnard. Improvements to gamut mapping colour constancy algorithms. In European conference on computer vision, pages 390–403. Springer, 2000.

[9] Jonathan T Barron. Convolutional color constancy. In Proceedings of the IEEE International Conference on Computer Vision, pages 379–387, 2015.

[10] Jonathan T Barron and Yun-Ta Tsai. Fast fourier color constancy. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 886–894, 2017.

[11] Simone Bianco, Gianluigi Ciocca, Claudio Cusano, and Raimondo Schettini. Improving color constancy using indoor-outdoor image classification. IEEE Transactions on image processing, 17(12):2381–2392, 2008.

[12] Simone Bianco and Claudio Cusano. Quasi-unsupervised color constancy. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12212–12221, 2019.

[13] Simone Bianco, Claudio Cusano, and Raimondo Schettini. Single and multiple illuminant estimation using convolutional neural networks. IEEE Transactions on Image Processing, 26(9):4347–4362, 2017.

[14] K Tiplitz Blackwell and G Buchsbaum. Quantitative studies of color constancy. JOSA A, 5(10):1772–1780, 1988.

[15] David H Brainard and Brian A Wandell. Analysis of the retinex theory of color vision. JOSA A, 3(10):1651–1661, 1986.

[16] Gershon Buchsbaum. A spatial processor model for object colour perception. Journal of the Franklin institute, 310(1):1–26, 1980.

[17] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In European conference on computer vision, pages 213–229. Springer, 2020.

[18] Turgay Celik and Tardi Tjahjadi. Adaptive colour constancy algorithm using discrete wavelet transform. Computer Vision and Image Understanding, 116(4):561–571, 2012.

[19] Ayan Chakrabarti, Keigo Hirakawa, and Todd Zickler. Color constancy with spatio-spectral statistics. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(8):1509–1519, 2011.

[20] Dongliang Cheng, Dilip K Prasad, and Michael S Brown. Illuminant estimation for color constancy: why spatial-domain methods work and the role of the color distribution. JOSA A, 31(5):1049–1058, 2014.

[21] Dongliang Cheng, Brian Price, Scott Cohen, and Michael S Brown. Effective learning-based illuminant estimation using simple features. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1000–1008, 2015.

[22] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghan, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.

[23] Graham D Finlayson. Corrected-moment illuminant estimation. In Proceedings of the IEEE International Conference on Computer Vision, pages 1904–1911, 2013.

[24] Graham D Finlayson and Elisabetta Trezzi. Shades of gray and colour constancy. In Color and Imaging Conference, volume 2004, pages 37–41. Society for Imaging Science and Technology, 2004.

[25] Peter Vincent Gehler, Carsten Rother, Andrew Blake, Tom Minka, and Toby Sharp. Bayesian color constancy revisited. In 2008 IEEE Conference on Computer Vision and Pattern Recognition, pages 1–8. IEEE, 2008.

[26] Arjan Gijsenij, Rui Lu, and Theo Gevers. Color constancy for multiple light sources. IEEE Transactions on image processing, 21(2):697–707, 2011.

[27] Chun-Le Guo, Qixin Yan, Saeed Anwar, Runmin Cong, Wenqi Ren, and Chongyi Li. Image dehazing transformer. In Proceedings of the IEEE conference on computer vision and pattern recognition, 21(2):697–707, 2011.

[28] Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.

[29] Arjan Gijsenij, Rui Lu, and Theo Gevers. Color constancy for multiple light sources. IEEE Transactions on image processing, 21(2):697–707, 2011.

[30] Chun-Le Guo, Qixin Yan, Saeed Anwar, Runmin Cong, Wenyi Ren, and Chongyi Li. Image dehazing transformer with transmission-aware 3d position embedding. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5812–5820, 2022.

[31] Yuanning Hu, Baoyuan Wang, and Stephen Lin. Fc4: Fully convolutional color constancy with confidence-weighted pooling. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4085–4094, 2017.

[32] Yuanning Hu, Baoyuan Wang, and Stephen S Lin. Fully convolutional color constancy with confidence weighted pooling, July 14 2020. US Patent 10,713,816.

[33] Xun Huang, Ming-Yu Liu, Serge Belongie, and Jan Kautz. Multimodal unsupervised image-to-image translation. In
