Polarized Color Image Denoising using Pocoformer

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Abstract. Polarized color photography provides both visual textures and object surficial information in one single snapshot. However, the use of the directional polarizing filter array causes extremely lower photon count and SNR compared to conventional color imaging. Thus, the feature essentially leads to unpleasant noisy images and destroys polarization analysis performance. It is a challenge for traditional image processing pipelines owing to the fact that the physical constraints exerted implicitly in the channels are excessively complicated. To address this issue, we propose a learning-based approach to simultaneously restore clean signals and precise polarization information. A real-world polarized color image dataset of paired raw short-exposed noisy and long-exposed reference images are captured to support the learning-based pipeline. Moreover, we embrace the development of vision Transformer and propose a hybrid transformer model for the Polarized Color image denoising, namely PoCoformer, for a better restoration performance. Abundant experiments demonstrate the effectiveness of proposed method and key factors that affect results are analyzed.

Keywords: real-world polarized color image dataset, image denoising, vision transformer

1 Introduction

A beam of light can be considered as a combination of linearly polarized lights oscillating in different planes perpendicular to the imaging plane. The polarized components are changed in specific ways up to the object refractive index and incident angle while they are reflected by dielectric materials. Therefore, polarized reflections convey information about object material properties and the surface geometries independent of light intensities and surface textures. For this reason, polarization photography plays a crucial role in transparent reflection removal \cite{29,23}, shape-from-polarization \cite{13,17} and so on.

The development of vision algorithms is inseparable from the progress of computation imaging techniques. Formerly, we were only able to capture chromatic or polarimetric information of a scene from several snapshots separately. Until a short while ago, the Sony’s polarized color sensors (e.g., IMX250MYR)
In the past decades, an amount of methods have been proposed for conventional image denoising. Traditional single image denoising methods \cite{33,11,30} try to model natural image priors with complicated hand-engineered algorithms. However, these models suffer from limited performance and high computation complexity. Another prevailing algorithmic approach is to employ a Deep Neural Network (DNN) for single-image-denoising in an end-to-end manner \cite{9,5,54,55}. Normally, deep learning approaches require a large set of noisy image and clean reference image pairs for model training. To the best of our knowledge, there has not been any real-world dataset released for tackling the low SNR problem of polarized color sensors. Also, though previous image denoising methods can handle noise signals in spatial dimension, restoring precise physical information from extremely noisy polarized color images still remains a challenge.

We collect a real-world dataset of noisy polarized color raw data. The corresponding clean images are captured with low-ISO long-exposure settings as ground truth. A learning-based pipeline is designed, which allows the model to be optimized under both chromatic and polarimetric constraints. Recent researches have illustrated that Transformer \cite{40} has enormous potentials in exploring global context interactions and outperforms convolutional DNNs in various
vision problems [15,28,6,28,8,26]. Therefore, we propose a Transformer model with hybrid attention mechanisms for effective polarized color image denoising, namely Pocoformer. The Hybrid Transformer Block (HTB) composed of self-attentions across spatial and channel dimension separately boosts both noise removal and polarization information restoration. We compare our method with traditional methods and recently proposed network architectures on the collected dataset. Furthermore, the ablation study analyzes critical factors in our method. The main contributions are as follows:

- A real-world dataset of noisy polarized color images in raw data format is captured, with corresponding reference images. Our dataset reveals the low SNR problem of polarization color imaging and corroborates the necessity of a learning-based denoising pipeline.
- We propose Pocoformer, a multi-scale hybrid transformer model for Polarized Color image denoising. Self-attentions across feature and spatial dimension are applied to boost signal denoising and polarization information restoration.
- We demonstrate the effectiveness of the proposed method and analyze key factors of the pipeline. Moreover, we also exhibit potential applications as the pre-processing of several downstream tasks.

2 Related work

2.1 Image Denoising

Image denoising is a well-researched yet still active topic in the computer vision community. Traditional single image denoising methods proposed elaborate models based on total variation [38], SVD [33], sparse coding [16], self-similarity [30], and so on. Recent researches mainly focused on the great capacities and expressiveness of CNNs, which adaptively learn data-driven denoisers from noisy images and their noise-free counterparts [9,34,55]. However, in real-world noise image processing scenarios, these methods have been proven to be outperformed by BM3D [11]. The reason is primarily that the learning-based models overfit to the synthetic training data constructed by over-simplified noise models [32]. Therefore, various researches captured short-/long-exposure image pairs to build dataset with real-world noises [32,7,1]. Some methods are also proposed for joint image demosaicing and denoising [18,27].

As far as we know, our work is the first research on addressing the noise issue of polarized color photography. There are some image restoration methods proposed for polarization images [24,52,2,53], but they can not handle polarized color images and lack of considerations on polarization properties. Polarization image demosaicing is more complicated than conventional image demosaicing. As the first work on polarized color image denoising, we neglect the mosaic issue.

2.2 Vision Transformer

Transformer was firstly proposed for the machine translation task [40]. Due to the ability of exploring long-term dependencies, Transformer-based networks became
prevalent in the realm of natural language processing (NLP) in no time \cite{14,48}. Inspired by the great success of NLP Transformers, some works introduced the self-attention layers into CNNs \cite{41,57} to explore global context interactions. In another line of work, Transformers taking over from spatial convolution layers partly/completely to build novel backbone architectures \cite{15,34}. Though these models slightly outperform the classic ResNet architecture \cite{19}, heavy computation costs still constrain the employment of self-attention layers in vision tasks. Until recently, Vision Transformer (ViT) \cite{15} utilized the Transformer technique on non-overlapping cropped image patches that achieved accurate yet efficient image classification. Proceeding one step further, local-window based Transformer models \cite{28,46,20} with various window partition strategies are proposed and achieved considerable improvements on the speed-accuracy trade-off. In SwinIR \cite{26}, Swin Transformer \cite{28} was used to build a single-scale architecture for high quality image restoration. Moreover, a lot of works \cite{6,42,49} tried to apply Transformers to build U-shaped networks that make further use of hierarchical structure of Swin and multi-scale skip connections of U-Net \cite{37}.

2.3 Exploiting Polarization

As polarization photography can capture more channels of information exhibited implicitly from environments, it has been extensively studied in both fields of computer vision and computer graphics. A few decades ago, polarization has been found to be effective in the image reflection removal tasks \cite{39}. More recently, learning based approaches \cite{29,23} using polarization cues have achieved reliable and powerful reflection separation performance. Furthermore, Shape-from-Polarization (SfP) has developed into a popular research area in recent years. Surface normal information encoded by light polarization was introduced into conventional 3D modeling pipelines \cite{10,47} and binocular stereo camera systems \cite{58,17} to produce more precise and complete geometries. Coupling polarization cues with CNNs, 3D object shape and human shape can be easily reconstructed with a single-view polarization image \cite{13,59}.

3 Dataset

**From pixels to polarization information.** We collect a raw image dataset using the FLIR BFS-U3-51S5PC polarized color camera for both training models and benchmarking polarized color image restoration. As shown in the Figure 1, the camera employs an IMX250MYR CMOS sensor and captures a single-channel raw image arranged in the Bayer-Polarization pattern. For each color, we sample the polarization pixels correspond to the angle of each polarizer (in turn of $90^\circ$, $45^\circ$, $0^\circ$ and $135^\circ$) and define their values as $I_{90^\circ}$, $I_{45^\circ}$, $I_{0^\circ}$, and $I_{135^\circ}$. Using the values, Stoke parameters can be calculated as follows for describing
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Unprocessed
Quantized
Nonlinearized

\[ S_0 \]
\[ \rho \& \phi \]
\[ S_0 \]
\[ \rho \& \phi \]
\[ S_0 \]
\[ \rho \& \phi \]

Fig. 2. Visual comparison of polarization information, intensity (\( S_0 \)), DoLP (\( \rho \)), AoP (\( \phi \)) extracted from unprocessed, quantized and nonlinearized data.

Unprocessed Quantized Nonlinearized
\( S_0 \)
\( \rho \& \phi \)
\( S_0 \)
\( \rho \& \phi \)
\( S_0 \)
\( \rho \& \phi \)

Fig. 3. Examples in our polarized color image dataset. The images are intensities \( S_0/2 \) in sRGB color space processed by color conversion and automatic white balance.

the polarization state of incident light:
\[
S_0 = \frac{1}{2} (I_{0^\circ} + I_{45^\circ} + I_{90^\circ} + I_{135^\circ}),
\]
\[
S_1 = I_{0^\circ} - I_{90^\circ},
\]
\[
S_2 = I_{45^\circ} - I_{135^\circ}.
\]  

(2)

It should be noticed that Stoke parameters build an interconnection among the individual polarization pixel values. Three components are mostly used for polarization information measurements, including the intensity of light (described by \( S_0 \)), the Degree of Linear Polarization (the proportion of fully linearly polarized light in a beam, DoLP, \( \rho \)), and the Angle of Polarization (the direction of polarization plane, AoP, \( \phi \)). \( \rho \) and \( \phi \) are calculated as:
\[
\rho = \sqrt{\frac{S_1^2 + S_2^2}{S_0}},
\]
\[
\phi = \frac{1}{2} \arctan \frac{S_2}{S_1}.
\]  

(3)

These information are essential for material property analysis and surface normal computations. Therefore, many downstream polarization-based computer vision algorithms directly take the measurements as their model inputs \[21,23,17\]. It is clear that the equations [1] and [3] only hold for unprocessed raw images or those processed by linear amplifications, e.g., digital gain and white balance. Non-linear computations in ISP, e.g., gamma correction and tone mapping, will completely destroy the implicit constraints. Moreover, the quantization process of converting 16-bit data to 8-bit values of bright images will introduce quantization noises and reduce accuracy, too \[43\]. As shown in Figure 2, we exhibit the rendered sRGB images and extracted polarization information of original raw data and processed data. Among the results, although quantization processing generates almost the same intensities, the diminished precision causes completely wrong \( \rho \) and \( \phi \). We apply gamma correction for data nonlinearization operation.
The intensity seems more pleasant to human vision, but the distribution of $\rho$ is noticeably changed. The results show negative effects of non-linear ISP and quantization on polarization information measurements.

**Dataset information.** Our dataset contains short-exposure noisy image and long-exposure reference (ground truth) image pairs of 106 scenes. The intensities are kept as 16-bit data that the data range is from 0 to 65535. For each scene, we mount the camera on a tripod and capture a reference image at first. Since the imaging quality changes according to different illumination conditions and environmental objects, the exposure time for capturing reference images are adaptively adjusted to collect sufficient photons. Then, two relatively short-exposure images are captured with the exposure time set as 1/10 and 1/100 of that of the long-exposed one, respectively. The number of distinct low-light images is 212. Since images in each scene require consistent contents throughout exposure time, all the environments are static. Certainly, other camera settings, (e.g., aperture, ISO, and focal length) are adaptively adjusted for the best imaging quality and remain unchanged in each scene. Since intensity level of images in each scene are adjusted by different exposing time, the miss-alignment problem almost does not exist in our dataset. Theoretically, by multiplying corresponding scale ratios, $\times10$ or $\times100$, the intensity distribution of the enhanced short-exposure image will be identical to that of the correspondent long-exposure image.

### 4 Method

#### 4.1 Pipeline

The pipeline of our method is illustrated in Figure 4. What we can obtain from a sensor as an input is a 16-bit full-resolution single-channel image arranged in the Bayer-Polarization pattern. To process raw data of Bayer pattern, it is a common choice for neural networks to pack the color values into four channels. The packing approach has been proven beneficial to network learning and able to reduce the computational cost of successive processes. For pixel values of different polarizers, they can be greatly diverse due to the distinct polarizer angles. Still, these intensities contain implicit interactions valuable for learning-based methods toward precise inferences. Therefore, we pack the pixels of different polarizers into four channels, too. As a result, the single-channel input is packed into 16 channels (${(90^\circ, 45^\circ, 0^\circ, 145^\circ)} \times \{R, G, B, G\}$) with a quarter of the input resolution in each dimension.
Subsequently, we amplify inputs by the extrinsically given scale ratio ($\times 10$ or $\times 100$) and feed them into our network. Notice that the amplification operation is linear and it does not change the polarization information. The output of the network is a 16-channel clean image. At last, the 16-channel image is post-processed by traditional image processing operations, e.g., white balance, color conversion, to generate visual results of different polarizers in the sRGB color space. Besides, polarization information $S_0$, $\rho$ and $\phi$ of each color are also calculated using raw outputs through equations \ref{equation:3}.

4.2 Network Architecture

Overall architecture As shown in Figure 5, our Pocoformer firstly extracts low-level feature embeddings with a $3 \times 3$ convolution layer. After that, 3 encoder stages, a bottleneck stage and 3 decoder stages, with successive Hybrid Transformer Blocks (HTBs) in each stage, are applied to handle multi-scale features. After each encoder stage and before each decoder stage, downsample layers and upsample layers, following the implementation of \cite{42}, are employed to reduce or recover feature resolutions. Low-level encoder features are delivered to the corresponding decoder stages, where the features of the former decoder are concatenated. Except for the last decoder stage, the channel of concatenated features are halved by a linear projection layer. At last, a $3 \times 3$ convolution layer is applied to output a residual to noisy input and generate a denoised image.
**Hybrid Transformer Block.** Different from conventional image denoising, polarized color image denoising aims to restore clean signals from noisy inputs while preserving precise polarization information at the same time. To meet the needs, we propose the Hybrid Transformer Block (HBT), which is build by stacking (Shifted) Window Multi-heads Attention ((S)W-MA), Window Multi-Shuffled-heads Transposed Attention (W-MT(S)A), and a Smoothing MLP (SMLP), as shown in the Figure 5b. While SW-MA is applied to capture spatial attention towards a better denoising performance, SW-MTSA is expected to model inter-connections of the channels and explore the polarization priors existed implicity in channle dimension. A LayerNorm (LN) layer is employed before each module (omitted in Figure 5) and a residual connection is applied after each module.

**Shifted Window based Multi-head Attention.** Conventional attention modules have shown great capabilities of modeling spatial long-term dependencies for image restoration tasks [57,12]. However, the time and memory complexity of the key-query dot-product is quadratic to the spatial resolution of input, that the global attention module is unavailable for our high resolution data. Compared with global attention, SW-MA has shown a better speed-accuracy trade-off [6] with local attention and shifted window strategy. Applying the learnable relative position encoding [6] B, the attention calculation can be formulated as:

$$\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T/\alpha + B)V,$$

(4)

where \(Q, K, V \in \mathbb{R}^{l^2 \times d}\) are the query, key and value matrices encoded with the same input; \(\alpha\) is a learnable temperature parameter for adjustable SoftMax activation; \(l^2\) denotes the window size and \(d\) represents the number of channels. As the stages get deeper, the SW-MA can capture longer spatial dependencies. Regular and shifted window partitioning are applied alternatively to facilitate interactions across windows.

**Window based Multi-Shuffled-heads Transposed Attention** While spatial attention focuses on modeling interactions of features in spatial domain, it neglects to explore physical characteristics existing implicitly in the channel dimension. Therefore, we propose W-MSTA to apply attention across channels. The transposed attention is defined as:

$$\text{TAttention}(Q, K, V) = V \cdot \text{SoftMax}(Q^TK/\beta),$$

(5)

where \(\beta\) is a learnable parameter, too. Since conventional multi-heads attention divides channels into multiple groups, the interactions through channels are insufficient. To tackle the issue, we introduce the channel shuffle operation [56] to enable intensive connections across channel groups. Following [56], the original features are firstly shuffled along the channel dimension, according to feature dimension and the number of heads. Then the channel-shuffled features are partitioned into non-overlapped windows and fed into the transposed attention module. Lastly, after the attention, the channel-enhanced features are shuffled back to the original arrangement.

**Smoothing MLP** The window participation approach can cause border artifacts even with shift operations, especially for sensitive polarization information. Thus, inspired by [25,42], we introduce a \(3 \times 3\) depth-wise convolutional layer
into conventional MLP layer \cite{40}. The depth-wise convolution is employed after the first linear projection layer and followed by GELU activation. The use of convolution layers in HTBs plays crucial roles in enhancing translation invariance in Transformer-based networks \cite{28,15}.

4.3 Loss Function

Given a noisy input \( x \) and its clean counterpart \( y \), a pixel-wise loss function is generally used to optimize a denoiser network. Here, loss function \( L_1 \) is formulated as follows:

\[
L_1 = \| y - F(x) \|_1,
\]

where \( F(\cdot) \) represents our network. The pixel-wise loss function aims to directly minimize the differences of pixels. However, there is polarization information implicitly stored in the channels, which is crucial for subsequent applications. While the pixel-wise loss focus on the differences of intensities, it poses weak constraints on polarization information. Therefore, inspired by \cite{45}, we minimize the Stoke parameter loss \( L_S \) of each color channel, which is formulated as follows:

\[
L_S = \frac{1}{4} \sum_{i=0,1,2,3} \| S(y_i) - S(F(x_i)) \|_1
\]

where \( S(\cdot) \) denotes computation of Stoke parameters, and \( i \) represents the number of four color channels (R-G-B-G). The intermediate variables provide a strong yet efficient constraint on polarization information. Thus, the final loss function \( L \) is as follows:

\[
L = L_1 + \lambda L_S,
\]

where \( \lambda \) is applied to balance two parts.

4.4 Training

The proposed network can be trained by an end-to-end strategy. The inputs of networks are packed raw data amplified by the correspondent ratio (\( \times 100 \) or \( \times 10 \)), and the ground truth are unprocessed clean raw images. They are scaled into the range of 0 to 1. The training procedure continues for 2000 epochs and the network is optimized by Adam \cite{22} optimizer with default settings. The learning rate is set to \( 10^{-4} \) at the first and is reduced to \( 10^{-5} \) after 1500 epochs. In each epoch, a \( 256 \times 256 \times 16 \)-sized patch is randomly cropped from a packed input. Random rotation and flipping are applied for data augmentation. The proportional weight \( \lambda \) in equation \( 8 \) is set as 1. More implementation details can be found in our supplemental.

5 Experiments

We compare our learning-based approach with a classic traditional single image denoising method and compare proposed network architecture with state-of-the-art single-image denoising networks. Notice that \( S_0 \) is calculated by averaging
Table 1. Polarized color image denoising performance in PSNR(dB)/SSIM calculated on 16-channel images, 4-channel ρ and 4-channel φ. **Bold** and **underlined** values present the best and the second best results, respectively.

| method          | image ρ   | image ϕ | #param. | FLOPs  |
|-----------------|-----------|----------|---------|--------|
| PCA [52]        | 24.56     | 19.51    | 8.41    |        |
| BM3D [2]        | 23.01     | 20.64    | 10.18   |        |
| M-BM3D [31]     | 22.96     | 22.81    | 11.34   |        |
| DnCNN-B [54]    | 32.22     | 15.36    | 9.14    | 684.52K| 180G   |
| U-Net [37]      | 35.82     | 22.70    | 10.26   | 7.76M  | 56G    |
| RDNet [24]      | 26.43     | 10.92    | 9.39    | 125.2K | 32G    |
| RIDNet [3]      | 38.65     | 23.65    | 11.50   | 1.51M  | 397G   |
| MIRNet [50]     | 39.15     | 24.79    | 12.26   | 31.80M | 3149G  |
| DeamNet [35]    | 37.78     | 23.89    | 12.11   | 2.24M  | 589G   |
| MPRNet [51]     | 38.68     | 25.06    | 12.29   | 15.79M | 2364G  |
| Uformer [42]    | 38.94     | 24.88    | 12.21   | 20.64M | 166G   |
| SwinIR [26]     | 38.95     | 25.04    | 12.29   | 11.55M | 2995G  |
| Restormer [49]  | 38.69     | 24.84    | 12.19   | 26.14M | 568G   |
| Ours-S          | 38.84     | 25.06    | 12.23   | 8.17M  | 184G   |
| **Ours**        | **39.33** | **25.32**| **12.34**| **26.26M**| **552G**|

all polarization images, which is the same as the operation of burst denoising. Therefore, in \( S_0 \) the noises will be exceedingly reduced which obstructs the observation on noises and processed results. Thus we directly compare performance on polarized color images, e.g., \( I_{90°} \) (same with values of any other polarizer angle), instead of using \( S_0 \).

5.1 Comparison with previous methods

We conduct experiments on our polarized color image dataset and report the comparing results. For enlarging the capacity, from first encoder stages to the last decoder stage, the number of stacked HTBs are [6, 8, 8, 8, 8, 8, 6], the number of channels are [48, 96, 192, 384, 192, 96, 48], and the number of heads are [1, 2, 4, 8, 4, 2, 2]. A light-weight architecture (Ours-S) with depths [2, 2, 2, 2, 2, 2, 2] and basic dimension 32 is also conducted. Peak Signal-to-Noise Ratio (PSNR) and Structure Similarity Index Measure (SSIM) are used for quantitative evaluations on restored images, DoLP (\( \rho \)), and AoP (\( \phi \)). We compare the previous algorithms, including traditional models PCA [52], BM3D [2] and M-BM3D [31], CNN-based models DnCNN-B [54], U-Net [37], RDNet [24], attention based models RIDNet [3], DeamNet [36], MIRNet [50], MPRNet [51], and Transformer models Uformer [42], SwinIR [26] and Restormer [49]. Secifically, PCA [52] and BM3D [2] are designed for polarized image denoising. Thus, the algorithm is applied on 4 chromatic channels (R,G,B,G) separately. As a contrast, we select M-BM3D [31] which can handle multple channel inputs. The most appropriate
noise levels are adjusted for the non-blind denoising methods. All the DNN models are trained with the same training setting. Model parameters and floating-point operations (FLOPs) are further analyzed in the experiment to evaluate the model complexity, as listed in the last two columns in Table 1. The FLOPs of DNN-based methods are computed with inputs of size $512 \times 512 \times 16$.

Table 1 shows quantitative results of polarized color image denoising. Compared with all previous methods, our network performs extremely well on both restoring clean images and precise polarization information. The results indicate that traditional methods suffer from weak denoising performance. Although BM3D outperforms M-BM3D on restored images, the polarization information are destroyed and underperform M-BM3D. Although our model outperforms DeamNet, MPRNet, SwinIR and Restormer by a considerable margin, our model takes a much less computation complexity. Especially, compared to SwinIR, our model decreases 81% of computation cost, the results yet outperform model on most metrics.

The visual comparison is shown in Figure 6. Traditional methods can remove noises to a certain degree, but fail to reconstruct polarization information. Due to the hybrid attention mechanism, our method is able to remove noises and restore the sharp details for both images and polarization information. In contrast, other methods tend to remove the details along with the noise, leading to oversmoothing images and losing details in polarization information.

### 5.2 Model generalization performance evaluation

There are other types of polarized color sensors and environments with different illumination conditions, but there is not any other released polarized color image...
Table 2. Quantitative results for polarized color image denoising on images captured with a different polarized color sensor, IMX264MYR.

| method | image | ρ | φ | PSNR(dB) | SSIM | ρ | φ | SSIM |
|--------|-------|---|---|----------|------|---|---|------|
| BM3D [2] | 24.47 | 21.31 | 9.29 | 0.914 | 0.376 | 0.095 |
| DeamNet [3] | 36.89 | 23.84 | 10.75 | 0.951 | 0.598 | 0.211 |
| MPRNet [5] | 38.59 | 26.22 | 11.13 | 0.962 | 0.668 | 0.246 |
| Uformer [4] | 39.92 | 25.67 | 10.89 | 0.965 | 0.645 | 0.231 |
| SwinIR [26] | 39.86 | 25.84 | 11.08 | 0.968 | 0.660 | 0.243 |
| Restormer [49] | 40.18 | 25.63 | 10.80 | 0.961 | 0.651 | 0.239 |
| Ours | **40.86** | **26.47** | **11.07** | **0.969** | **0.666** | **0.246** |

Fig. 7. Visual comparison for model generalization evaluation. The input data are captured with a different polarized color sensor IMX264MYR.

dataset with real-world noises. Thus, we captured another evaluation set with a different polarized color camera, LUCID VISION TRI050S1-QC equipped with IMX264MYR sensor, under low-light street lighting conditions and directly evaluate our trained model on it. BM3D and well-performed DNN models in section 5.1 are selected for a comparison.

Table 2 shows the quantitative comparison. Our model still outperform other methods by a great margin on noise removal and polarization information restoration. The visual comparison is shown in Figure 7. It should be noticed that for restored images, while the other results suffer from extremely noticeable inconsistent color distribution and severe blurs, our result have natural color and clean textures. We give the credit to our Hybrid Transformer Block and SMLP. The first one gets physical constraints across the channels involved in using attention mechanism, and the second one smooths border artifact introduced by local attention. See more details in section 5.3.
Table 3. Quantitative results for ablation experiments.

| Network                        | w/o $\mathcal{L}_S$ | PSNR(dB) | \(\rho\) | \(\phi\) |
|-------------------------------|----------------------|----------|----------|----------|
| (a)W-MA +MLP                  | -                    | 38.39    | 24.33    | 11.99    |
| (b)W-MTA +MLP                 | -                    | 38.16    | 24.06    | 11.97    |
| (c)W-MA +W-MTA +MLP           | -                    | 38.42    | 24.41    | 12.03    |
| (d)W-MTA +W-MA +MLP           | -                    | 38.26    | 24.29    | 12.02    |
| (e)W-MA +W-MTA +SMLP          | -                    | 38.40    | 24.33    | 12.03    |
| (f)SW-MA +W-MTA +SMLP         | -                    | 38.53    | 24.67    | 12.16    |
| (g)SW-MA +W-MSTA +SMLP        | ✓                    | 38.64    | 24.49    | 12.05    |

5.3 Ablation Study

For a convenient ablation study, a lightweight structure is used, in which from level 1 to 4, the number of stacked HTBs are [2,2,2,2] and the number of channels are [32,64,96,128]. The model variations are trained following the same setting described in section 4.4. Table 3 shows that our contributions yield quality performance improvement for polarized color image denoising.

**Hybrid Transformer Block.** We apply attention mechanisms for capturing long-term dependencies in both spatial and channel domain. Table 3(a-c) demonstrates that the combination of two types of attention mechanisms provide favorable gain over the network with arbitrary single attention mechanisms on both noise removal and polarization information restoration. Furthermore, (c) and (d) prove the order the two attention mechanisms also slightly affect the performance.

**Smoothing MLP.** Compared with (d) in Table 3, SMLP (e) causes slight performance degradation on denoised images. Moreover, Figure 8(d) and (f) shows the results with MLP and SMLP, which prove the smoothing effect of SMLP on both restored images and polarization information.

**Shifted window and shuffled heads.** Results in Table 3(e-g) demonstrate these operations provide considerable performance gain and benefit to more precise polarization information restoration. Moreover, Figure 8(f) and (g) illustrates that window shift and channel shuffle strategies effectively reduce border artifacts and eliminate the inconsistent color distribution, especially the latter one.

**Stoke parameter loss.** A loss function combining pixel-wise differences and polarization information errors are applied to optimize the network. (g) and (h) in Table 3 shows the performance of the model trained with and without $\mathcal{L}_S$. The comparison demonstrates that $\mathcal{L}_S$ lead to slight performance degradation on image denoising, but benefit to preserve precise polarization information, which is more important for downstream tasks.
5.4 Applications

Here, we show our denoising approach can be beneficial to downstream polarization-based algorithms, both of which have indicated their method is robust to noises. **SfP.** We feed a noisy and denoised polarization image into a 3D shape reconstruction network [13]. As illustrated in Figure 9 compared with the noisy input, the 3D normal reconstructed with our denoising process contains a more detailed structure and accurate shape. Quantitative results on PSNR are also shown in the Figures.

**Reflection removal.** We further test our denoised images on a polarization-based reflection separation algorithm [29]. The results are exhibited in Figure 10. As shown in enlarged regions, reflection removal results with our denoised input has very close performance to results with a clean input, containing sharp details and clear edges in separated images compared to results of noisy input.

6 Conclusion

In this paper, we address the low SNR issue of polarized color sensors. We propose a learning-based pipeline to simultaneously restore clean signals and polarization information. A real-world polarized color image dataset of paired raw
short-exposure noisy and long-exposure reference images are captured to support the learning-based pipeline. Moreover, we embrace the development of vision Transformers and propose a U-shaped Transformer network build by Hybrid Transformer Blocks. Self attention modules across spatial and channel dimensions are proposed for removing noisy signals and restoring precise polarization information. Experimental results show that our proposed method outperforms traditional and recently proposed DNN-based single-image denoising methods on the polarized color image denoising task. Extensive ablation studies proven our contributions. We also demonstrate that our denoising process benefits subsequent polarization applications. We hope our work can inspire future researches on polarized color image restoration.

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