Multi-scale Dynamic Feature Encoding Network for Image Demoiréing

Xi Cheng, Zhenyong Fu and Jian Yang
PCA Lab, Key Lab of Intelligent Perception and Systems for High-Dimensional Information of Ministry of Education, and Jiangsu Key Lab of Image and Video Understanding for Social Security, School of Computer Science and Engineering
Nanjing University of Science and Technology, Nanjing, China
{chengx,z.fu,csjyang}@njust.edu.cn

Abstract

The prevalence of digital sensors, such as digital cameras and mobile phones, simplifies the acquisition of photos. Digital sensors, however, suffer from producing Moiré when photographing objects having complex textures, which deteriorates the quality of photos. Moiré spreads across various frequency bands of images and is a dynamic texture with varying colors and shapes, which pose two main challenges in demoiréing—an important task in image restoration. In this paper, towards addressing the first challenge, we design a multi-scale network to process images at different spatial resolutions, obtaining features in different frequency bands, and thus our method can jointly remove moiré in different frequency bands. Towards solving the second challenge, we propose a dynamic feature encoding module (DFE), embedded in each scale, for dynamic texture. Moiré pattern can be eliminated more effectively via DFE. Our proposed method, termed Multi-scale convolutional network with Dynamic feature encoding for image DeMoiréing (MDDM), can outperform the state of the arts in fidelity as well as perceptual on benchmarks.

1. Introduction

Photographing with a mobile phone or digital camera often generates moiré, which seriously affects the visual quality of captured images. Moiré usually appears in the form of colored stripes, changing significantly due to the angle and distance of the shot. Using a digital camera or mobile phone to shoot a computer or TV screen exemplifies the moiré phenomenon where moiré appears more obviously. Since the screen is composed of LED lattices and the Color Filter Array (CFA) of camera’s sensor also has a certain texture structure, the imperfect alignment [18] between them mainly causes the generation of moiré pattern. Figure 1 gives a visualization for the formation of the moiré pattern. The left and right rings in Figure 1 generate different moiré patterns result from different misalignment and show the dynamic and variable characteristics of moiré patterns.

Demiöréing differs from traditional image restoration tasks such as denoising and super-resolution. The latter is usually static, with relatively consistent degradation on the image, while moiré is often dynamic and will vary with sensor resolution, distance, and direction. Moreover, the frequency distribution of moiré is broad, covering both the low-frequency part and the high-frequency part, while the tasks such as image denoising and super-resolution only need to process the high-frequency part of images. Therefore, demoiréing is more difficult than other image restora-
To remove the moiré pattern in images, we construct an image feature pyramid, encode image features at different spatial resolutions, and obtain image representations of different frequency bands. Specifically, we propose a multi-scale residual network with multiple resolution branches. These branches learn the nonlinear mapping on the original resolution and the $2 \times, 4 \times, 8 \times, 16 \times$ and $32 \times$ downsampled resolutions. Then, the features are up-sampled to the original resolution with sub-pixel convolution [14] at the end of each branch. The network automatically learns the weight of each branch and eventually sums the results from different resolutions to get the final output, i.e., the demoiréing image.

The moiré pattern is a dynamic texture. To encode the moiré pattern dynamically, we propose a dynamic feature encoding (DFE) module. Especially, at each down-sampling branch, we introduce an extra lightweight branch. The number of convolutional layers in this extra branch equals to the number of residual blocks in the backbone branch. Each dynamic feature coding branch encodes the characteristic of the global residual at different scales. In the end, we impose the coding of the dynamic moiré pattern back to the main branch through adaptive instance normalization (AdaIN) [7, 16] to guide the demoiréing process. Figure 2 gives a visualization of our demoiréing method which effectively removes the moiré patterns in the image.

We summarize our main contribution in the following points:

- We propose a novel method to remove moiré pattern through a progressive multi-scale residual network which enables the model to learn the representations on multiple frequency bands.

- We further propose a dynamic feature encoding (DFE) module that can encode the variations of moiré patterns in images so that the model can better cope with the variability of moiré pattern.

- The proposed method outperforms the state of the art and achieves the 2nd place in the AIM2019 Demoiréing Challenge [21] - Track 1: Fidelity and the 3rd place in Track 2: Perceptual.

We organize the rest of this paper as follows: Section 2 discusses the researches related to this article, and Section 3 elaborates the structure of the proposed demoiréing network. Section 4 shows our experimental results. In Section 5 we study the internal parameters and structure of the network. Section 6 concludes our paper.

2. Related Work

Image restoration is an important task in low-level vision. In image restoration, a large number of recent researches mainly focus on tasks such as image super-resolution [4, 12, 14], image denoising [23], and image deblurring [9]. Demoiréing is also an important image restoration task and is even more difficult than other image restoration tasks. However, in recent years, demoiréing has received rare attention; relatively few related studies focus on this topic.

Traditional demoiréing approaches are mainly based on filtering or image decomposition methods. Wei et al. [17] proposed a median-Gaussian filtering method for eliminating moiré in X-ray microscopy images. Liu et al. [13] applied a low-rank and sparse matrix decomposition-based method to remove moiré on texture images. Yang et al. [19] proposed a layer decomposition method based on polyphase components (LDPC) to better remove the moiré generated when shooting the screen.

Deep neural networks have promoted many computer vision tasks greatly compared with traditional methods. Deep convolutional neural networks have been used in image restoration tasks in recent years. Sun et al. proposed a demoiréing network based on multi-scale convolutional neural networks [15] and a large moiré image dataset based on ImageNet [3]. This network provided an impressive result in removing moiré pattern. Later, Gao et al. [5] improved the multi-scale framework with feature enhancing branch [24] which enhanced semantic information with a fusion of low and high level features. However, their proposed method do not have strong network architectures, the feature expression ability is weak, and the characteristics of the input image cannot be fully extracted. Moreover, they used transposed convolution [22] for up sampling which cannot usually cannot make good use of the information and causes artifacts in the generated images. Liu et al. [12] proposed a method for removing moiré pattern based on a deep convolutional network for screenshot images. Their proposed method could effectively remove most of the moiré noise. However, they only used a low-resolution scale input and could only characterize the moiré in a single frequency band. The frequency of the moiré is widely distributed, and thus the moiré pattern cannot be well removed in their method.

To overcome the limitations in existing demoiréing
methods, we propose two vital schemes: a multi-scale or multi-resolution network structure and a dynamic feature encoding module. The multi-resolution network, aiming at processing the moiré image at multiple resolutions, and the dynamic feature coding module, aiming at encoding the variability of dynamic moiré patterns, benefit from each other for removing moiré. We will detail our proposed method in the next section.

3. Proposed Method

Our proposed demoiréing network is a multi-branch structure that can be considered as a single encoder and multi-decoder structure. We use an encoder to downsample the input moiré image to $\frac{1}{2}$, $\frac{1}{4}$, $\frac{1}{8}$, $\frac{1}{16}$, and $\frac{1}{32}$ of the original resolution, encoding image features in different frequency bands. Two key parts in our proposed method, multi-scale structure and dynamic feature encoding will be elaborated in Section 3.1 and Section 3.2 respectively.

3.1. Multiscale residual network

The existence of moiré often lies in the imperfect alignment between the repetitive structure or texture of objects being photographed, e.g. the LED array of the screen, and the Bayer array on the camera sensor [18]. The moiré pattern is distributed throughout the low- and high-frequency portions of an image. Continuously downsampling the image, image representations from high frequency to low frequency will be separated. Figure 3 visualizes the representations of different frequency bands decomposed from the original image. If we only demoiré at the original resolution, more high-frequency details of images will be retained, but the low-frequency moiré pattern will be difficult to be removed cleanly. On the contrary, although demoiré after downsampling can make the image cleaner, the demoiré image will lose more high-frequency details. Therefore, the demoiréing network must learn the representations of different frequency bands at different resolutions. After combining the demoiré results at various resolutions, the reconstructed image can cleanly remove moiré and in the meanwhile maintain more image details.

To handle the demoiréing task, we construct a six-branch fully convolutional network containing the original resolution and $2 \times$, $4 \times$, $8 \times$, $16 \times$ and $32 \times$ down-sampled resolutions. According to the spatial size of the input feature, the higher resolution branch will have more computational complexity than the lower resolution branch in the same network structure. The higher resolution branch itself retains more high-frequency information, and the lower resolution branch needs a deeper network structure to recover more useful high-frequency information. Thus, we build a progressive network structure as shown in Figure 4. High-resolution branches have fewer convolutional layers, and low-resolution branches have more convolutional layers and more complex structures.

In our model, Branch-0 remains the original resolution and only uses a 3-layer convolution structure. The calcula-
The structure of our proposed Channel attention Dynamic feature encoding Residual block (CDR).

The operation of channel attention can be divided into the squeeze and excitation parts, as defined in Eq. 3 and Eq. 4, respectively.

Figure 5. The structure of our proposed Channel attention Dynamic feature encoding Residual block (CDR).

The calculation process of Branch-0 is:

$$F_0 = \sigma^p W_3 (\sigma^p W_2 (\sigma^p W_1 (I))),$$  \hspace{1cm} (1)

where $F_0$ is the output feature generated from Branch-0, $I$ denotes the input image, $\sigma^p$ means PReLU activation function and $W$ means the weight of convolution layers in the branch. The resolution of Branch-1 is half of the original, using two residual blocks and increasing channel attention. The calculation process of Branch-1 can be expressed as follows:

$$F_1 = U p(C D R_3(C D R_2(C D R_1(D o w n(F_0)))) + D o w n(F_0)),$$  \hspace{1cm} (2)

where $F_1$ and $F_{i+1}$ denote the output feature from the adjacent branch with higher resolution and the output feature of the current branch, respectively. $D o w n(\cdot)$ is the downsample block and $U p(\cdot)$ is the upsample block. $C D R$ is the abbreviation of Channel attention Dynamic feature encoding Residual block, of which the structure is shown in Figure 5. The operation of channel attention can be divided into the squeeze and excitation parts, as defined in Eq. 3 and Eq. 4 respectively.

$$S(x_c) = \frac{1}{H W} \sum_i^H \sum_j^W x_c (i, j),$$  \hspace{1cm} (3)

where $S(\cdot)$ represents the squeeze process with global average pooling. $H$ and $W$ denote the height and width of the feature map, and $x_c$ means channel $c$ of the input feature map $x$.

$$A_c(x) = \sigma^s (W_a \sigma^p (W_d S(x))) * x,$$  \hspace{1cm} (4)

where $A_c(\cdot)$ denotes the channel attention function, $\sigma^p$ means the PReLU function, $W_a$ and $W_d$ denote two $1 \times 1$ convolution layers containing 1/16 of the original channels to form a bottleneck, $\sigma^s$ means the sigmoid function which maps the features between 0 to 1, and we use these features as a weight to refine the original information in the residual.

The structures of Branch-2 to Branch-5 are similar to Branch-1, except that the number of residual blocks is increased, corresponding to spatial resolutions of 1/4, 1/8, 1/16, and 1/32, respectively:

$$F_{i+1} = U p(N L(D o w n(C D R_k \ldots (C D R_1(F_i) + F_i)))),$$  \hspace{1cm} (5)

where $F_i$ and $F_{i+1}$ denote the feature from the adjacent branch with higher resolution and the feature of the current branch, $C D R_k$ means the $k$-th block in the branch, $N L(\cdot)$ means the region-level non-local operation at the end of the branch, which helps the model learn self-similarity in the current resolution.

### 3.2. Dynamic feature encoding

Demoiréing differs from traditional image restoration tasks, such as super-resolution and denoising. Moiré is a dynamic pattern in that the interference texture on an image is local and varies with scaling and angle. In contrast, the restoration pattern of super-resolution or denoising is static, because if a specific degeneration model, e.g. bicubic downsampling and Gaussian noise, is used, the effect on the entire image is often consistent.

In this paper, we propose a dynamic feature encoding (DFE) module to enhance the ability of our demoiréing model to cope with dynamic textures. The global residual learning is used internally in the branch of each resolution in our proposed network. We use the residual block to model the difference between the clean and moiré images at each feature level and frequency band, that is, the moiré pattern on each branch. The inconsistent nature of moiré affects the learning of demoiréing network, and is more intense than other image restoration tasks.

Inspired by the recent work in arbitrary image style transfer, we design a bypass branch for each main scale branch to encode image features at different spatial resolutions. We embed the extra bypass branch into each backbone resolution branch using adaptive instance normalization (AdaIN). Specifically, in AdaIN, we first calculate the mean value and the variance of the feature map as follows:

$$\hat{\mu}_i = \frac{1}{H W} \sum_{j=1}^H \sum_{k=1}^W x_{i,j,k}^{enc},$$  \hspace{1cm} (6)

and

$$\hat{\sigma}_i^2 = \frac{1}{H W} \sum_{j=1}^H \sum_{k=1}^W (x_{i,j,k}^{enc} - \hat{\mu}_i)^2,$$  \hspace{1cm} (7)

where $H$ and $W$ denote the height and width of the feature map, $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the mean value and the variance of feature $x_i^{enc}$ from the $i$-th encoding layer in the dynamic feature encoding branch. After we calculate the statistical values of the moiré pattern, we use these values to dynamically adjust the parameters of the backbone resolution branch via adaptive instance normalization as follows:

$$x_{i+1} = \frac{x_i - \hat{\mu}_i}{\sqrt{\hat{\sigma}_i^2 + \epsilon}} \sqrt{\hat{\sigma}_i^2} + \hat{\mu}_i,$$  \hspace{1cm} (8)
where $\mu_i$ and $\sigma_i^2$ denote the statistical information from the backbone branch, and $x_i$ denotes the feature map from the $i$-th residual block in the backbone branch. Section 5.2 gives an experimental analysis of dynamic feature coding.

### 3.3. Reconstruction network and loss function

Different branches learn feature representations at different resolutions. The distributions of moiré pattern and the image details on different resolution branches are all different. Thus, we design a branch scaling module that can automatically learn the importance of each branch with backpropagation, giving each branch an importance weight. The reconstruction process of the final demoiréing image is represented in Eq. 9 as follows:

$$\hat{I} = S_0(F_0) + ... + S_6(F_6),$$  \hspace{1cm} (9)

where $\hat{I}$ is the reconstructed clean (demoiréed) image, $S(.)$ is the scaling function, $F_i$ is the output feature of each branch. Since directly optimizing the mean squared error (MSE) is easier to make the image over smooth and thus blur, we instead minimize the Charbonnier loss [10]. Specifically, this loss function is defined in Eq. 10.

$$\text{Loss} = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(\hat{I} - I)^2 - \epsilon^2},$$  \hspace{1cm} (10)

where $N$ denotes the batch size, $\hat{I}$ and $I$ denote the demoiréed image generated from the reconstruction network and the ground truth image without moiré, respectively, and $\epsilon$ is a parameter in charbonnier penalty and is set to 0.001 in our experiments.

### 4. Experiment

#### 4.1. Dataset and train detail

We use the LCDMoire dataset [20] provided by the AIM contest as the training and validation sets, without using any additional datasets. We use pytorch1.2 to build our proposed MDDM model and use NVIDIA Titan V GPU with CUDA10.0 to accelerate training. We use the Adam optimizer when training the model. We first train a basic model which only contains three branches for feature decomposition and demoiréing. The initial learning rate is 1e-4, and the learning rate is reduced by 10 times for every 30 epochs. Then we further increase the network size gradually to 4, 5 and 6 branches, and then finetune these models on the previous basis. On the finetuning stage, the learning rate is set to 1e-5 and is reduced by 10 times for every 50 epochs.

#### 4.2. Comparison with the state of the arts

In this section, we compare our proposed MDDM with some deep learning-based demoiréing methods [5, 15] proposed in recent years. Image demoiréing is also related to image denoising [23], and thus we compare our method with DnCNN. For a fair comparison, all of the above meth-

|          | DnCNN | MSFE | Sun | Ours |
|----------|-------|------|-----|------|
| PSNR     | 29.08 | 36.66| 37.41| 42.49|
| SSIM     | 0.906 | 0.981| 0.982| 0.994|

Table 1. Performance comparison with DnCNN [23], MSFE [5] and Sun [15] on the LCDMoire [20] validation set.
| Scale   | PSNR  | Parameter | Computation |
|---------|-------|-----------|-------------|
| 1       | 27.71 | <0.01     | 0.17        |
| 1+2     | 27.89 | 0.77      | 187.17      |
| 1+2+4   | 35.71 | 1.90      | 288.45      |
| 1+2+4+8 | 38.22 | 3.54      | 358.68      |
| 1+2+4+8+16 | 42.48 | 5.70      | 417.58      |
| 1+2+4+8+16+32 | 42.49 | 8.01      | 472.38      |

Table 2. Performance (dB), parameters (M) and computation (GFLOPs) with different numbers of branches.

| Structure | PSNR  | Parameter | Computation |
|-----------|-------|-----------|-------------|
| No DFE    | 39.30 | 6.94      | 393.14      |
| DFE       | 42.49 | 8.01      | 472.38      |

Table 3. Performance (dB), parameters (M) and computation (GFLOPs) with and without dynamic feature encoding (DFE).

| Branch   | Parameter | Computation |
|----------|-----------|-------------|
| Branch1  | 0.11      | 12.68       |
| Branch2  | 0.27      | 15.90       |
| Branch3  | 0.58      | 16.70       |
| Branch4  | 0.77      | 16.95       |
| Branch5  | 1.07      | 17.01       |

Table 4. Model parameters (M) and computation (GFLOPs) of each branch with DFE.

ods are retrained on the LCDMoire training set and are evaluated on the LCDMoire validation set. We use the peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) [25] as the performance evaluation indicators. The result is shown in Table 1. From Table 1 it can be seen that the results of our proposed MDDM are significantly better than the state of the arts.

4.3. Visual results

In this section, we compare the visual results of our proposed MDDM with the above mentioned demoiréing methods. The visual results are shown in Figure 6. The red square means zoom-in of the image such that we can compare the details of the results. From left to right are the moiré image, results of DnCNN [23], MSFE [5], Sun [15], our proposed MDDM and the ground truth. PSNR and SSIM are shown under the image. The visual results show that our proposed MDDM is significantly better than other methods. Our MDDM removes moiré patterns more cleanly, while other methods bring more artifacts or can’t completely remove moiré patterns.

5. Ablation Study

In this section, we study the structural design in our proposed model. We analyze the modules we designed from the perspectives of performance, model parameters, and computation. In Section 5.1 we conduct experiments on the number of branches. In Section 5.2 we analyze the performance gain brought by the DFE module, the computational burden, and parameter growth.

5.1. Network branches

Different branches learn image features at different resolutions and encode image representations at different frequencies, and therefore the number of branches significantly affects the performance of the model. In this section, we study the relationship between model performance and network branches. The results are shown in Table 2. We use PSNR as an indicator of performance. We also compare the number of parameters and the number of single-precision floating point (FP32) calculations. The experimental results are shown in Table 2.

At the end of the network, we have designed a scaling module to automatically learn the weight of each branch. These weights can be viewed as the indicators of the importance of branches for the final reconstruction or demoiréing image. Figure 7 visualizes the weight of each branch. We can see that branches with higher resolutions are of greater importance.

5.2. Dynamic feature encoding

To cope with the dynamics of moiré, we use dynamic feature encoding (DFE) branches to encode the dynamic properties of moiré. We analyze the demoiréing performance and model complexity with and without DFE. The experimental results are shown in Table 3. Dynamic feature encoding (DFE) is a lightweight module which will not bring much model parameters and computation. Table 4 shows the parameters and calculations growth after adding DFE to each branch.
6. Conclusion

Digital cameras and mobile phones make photography more convenient in life, but digital sensors often produce moiré when shooting scenes with repetitive textures such as screens, which seriously affects the quality of shooting. Moiré patterns are more variable and dynamic, and therefore demoiréing is more challenging than other image restoration tasks. In response to this task, this work proposes a new demoiréing method, which includes two key elements: multi-scale residual network and dynamic feature coding. Multi-scale networks remove moiré in different bands and preserve more image detail. Dynamic feature coding allows the model to adapt to the changing nature of the moiré. It can be seen from the test results that the model gain larger than 3dB in PSNR after adding the DFE branch, and DFE is a lightweight module, which only brings a limited increase in the number of parameters and computation. Through the benchmark data, our proposed model can effectively remove moiré and outperform the state of the arts.

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