DeepWPD: A Deep learning based Wavelet Packet Decomposition to Remove Moiré Pattern from Screen Capture Images.

by

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in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

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Declaration

It is hereby declared that

1. The thesis submitted is my own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Approval

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Abstract

Moiré artifacts is a special type of noise which is rarely considered in deep learning based image processing tasks. But with the increasing number of digital screens like TV, laptop, desktop screens etc. it is becoming common to take pictures of these screens to quickly save information and a common aliasing effect in these screen capture images is moiré pattern. These kinds of artifacts in images appear when two repetitive patterns interfere with one another. Moiré patterns degrade the quality of photos. It affects the performance of other deep learning tasks using these images like classification, segmentation etc. As the moiré pattern is highly variant, has imbalanced magnitude in different channels and sophisticated frequency distribution, they are difficult to be completely removed without affecting the main information of the underneath image. Because of its complex nature, most state-of-the-art image restoration and denoising related methods fail to remove these artifacts. In this paper I proposed an effective wavelet based deep learning model for removing moiré patterns which outperforms all other state of the art by large margins. My proposed model recovers the details of the moiré free image using the wavelet packet transform. The Residual Dense Module Network and Dilation Convolution Network of our model acquires moiré information from almost all frequency ranges. One for high frequency range and other for low frequency range.

Keywords: Moiré artifact; Deep learning; Screen capture; Wavelet; Convolution Network; Dense Network; Denoising

Dedication

I would like to dedicate this thesis to our loving parents, supervisor, co-supervisor and everyone out there who helped me throughout our work.

Acknowledgement

First of all, I would like to thank Almighty Allah, as I could work on this thesis which has been a great learning experience for me. By the grace of Allah, I was able to put our best efforts and successfully complete it on time. Secondly, I would like to convey our gratitude to my supervisor Jannatun Noor for her handful contributions throughout my thesis work. From the very beginning, she has inspired me to move forward to our goal. Finally, I would like to thank my parents for their love and support.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

$CFNet$ Context fusion network

CNN Convolutional Neural Networks

DCN Dilation Convolution Network

$DeepWPD$ Deep learning based Wavelet Packet Decomposition

$DRDN$ Directional Residual Dense Network

DWT Discrete Wavelet Transform

$IRNN$ Image Recurrent Neural Network

$IWPT$ Inverse Wavelet Packet Transform

$PSNR$ Peak Signal-to-Noise Ratio

RDB Residual Dense Block

$ResNet$ Residual neural Network

$RRCNN$ Recurrent Residual Convolutional Neural Network

SR Super-Resolution

$SSIM$ Structural Similarity Index Measure

WPD Wavelet Packet Decomposition

WPT Wavelet Packet Transform

Chapter 1

Introduction

1.1 Background

Because of the widespread use of social media usage and smartphone user digital image carries a lot of useful information. These images are taken in a variety of environments. Because of that, these widely available digital images contain a variety of noises. One such kind of noise in an image is aliasing effect [1]. A category of the aliasing effect is moire pattern. These are the images where a person takes shots of a program happening on their TV as shown in figure 1.1(a) our own captured image and (b) screen captured image from TIP2018 dataset. This kind of pattern can happen because of frequency aliasing[1]. Artificial low-frequency moire patterns can also appear because of undersampling. Superimposed color variation into an image can be another reason for moire pattern. Also the intercession between the pixels of the screen and sensor of the camera can produce these artifacts as it is seen in the figure 1.2[22]. In general moire patterns can be seen in the photographs of fabrics, architecture, any fine patterns as well as capturing images of a TV screens/ Monitors.

Figure 1.1: Moiré artifacts in (a) my own screen captured image and the picture (b) is a screen captured image from TIP2018 dataset.

In figure 1.3 we can see the moiré artifacts in pattern structures in texture images. where (a) shows moiré artifacts because of the placement of two different directional

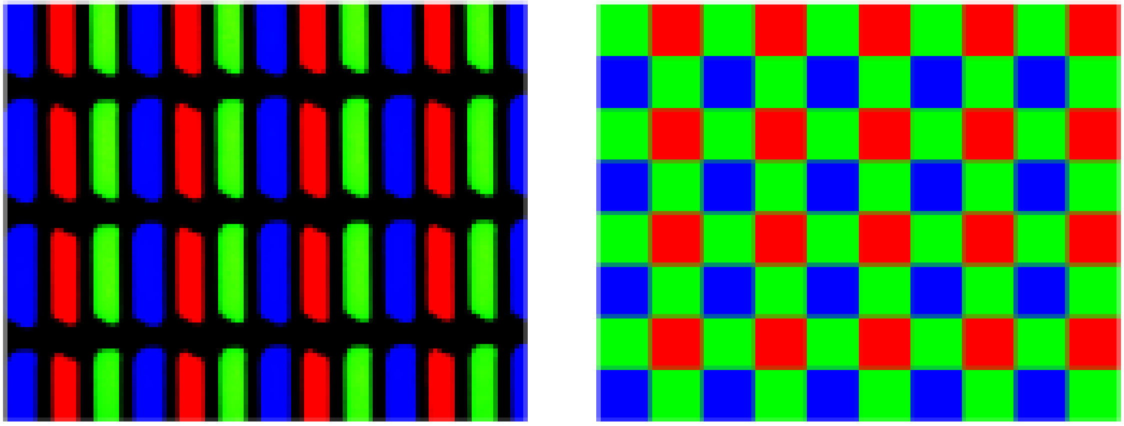

Figure 1.2: LCD subpixel structure (left) and camera Bayer CFA (right)

gratings over each other. Where in (b) we can see moiré artifacts on a pattern like texture photos taken by a digital camera. As we can see there are wave-like color structures in the textured image and if we decompose it in RGB channels we can see the different moiré patterns with different characteristics.

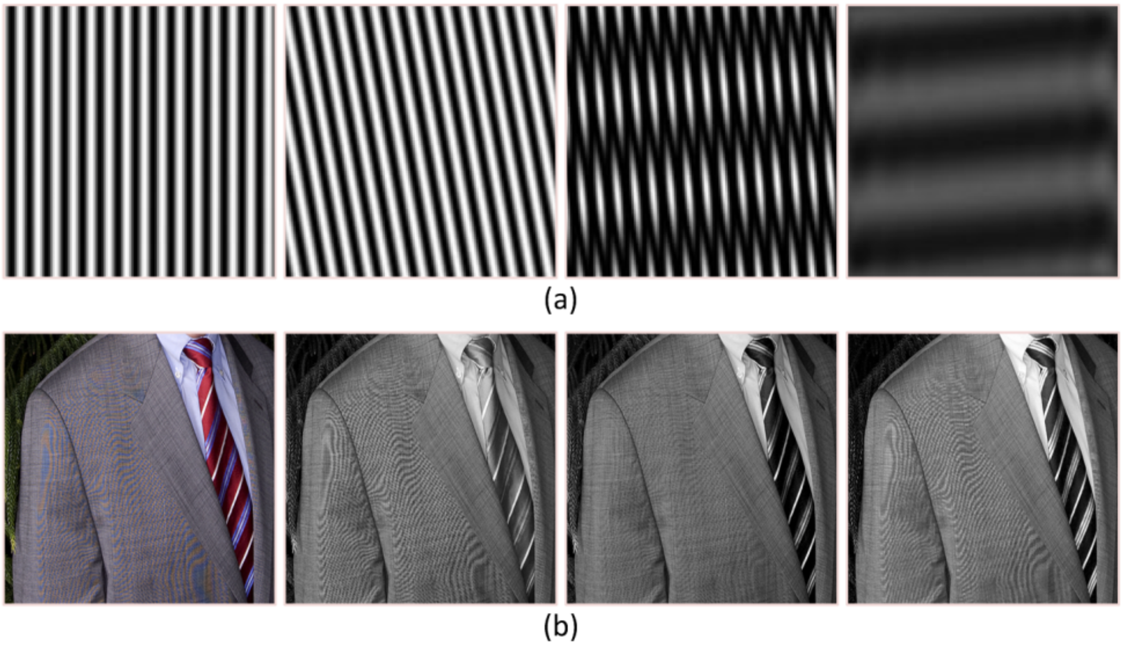

Figure 1.3: (a) shows moire patterns because of the placement of two different gratings. Illustrated from left to right, cosine grating image as i1 ,cosine grating image as i2 , combined image i3 consist of images i1 and i2 and lastly moire pattern separated from image i3. In (b) from left to right: a color textured image with moire artifacts, and the red (R), green(G), blue (B) channels of the image.

1.2 Research Problem

To reduce the moire pattern some cameras have a low pass filter or anti-aliasing filter on them, which compromises the image quality. Moreover this filter has limited capabilities. There are some approaches like low rank and sparse matrix decomposition[13] . But these methods are unable to remove complex moire patterns. In some cases deep learning approaches fail if the images in datasets contain images from a variety of camera setups. The main challenge of moire pattern then any other noise is it varies from image to image. Most of the time the direction of moire patterns changes depending on the different locations in an image as well as different frequencies in the same image. Because of this particular property of moire pattern, deep convolutional neural networks based approaches fail because for any deep convolutional neural network requires similar pairs of moire pattern affected images. All these complex properties of moire pattern creates a difficult challenge to remove the pattern from an image. On one such approach by Liu et.al [22] they determined the main structure of moire patterns while capturing an image of a screen. This approach may fail to remove moire artifacts from any other type of images. All these moire patterns eventually degrade the quality of images. It becomes hard to do other deep learning tasks using these images like classification.

1.3 Research Objective

In this paper our aim is to develop an effective and efficient method for removing moire patterns. The research objectives are as follows:

- Build a model to remove screen captured moire effects from a wider range of frequencies.
- Recovering structural details of noise free images using wavelet packet decomposition.
- Removing coloured moiré artifacts.
- Recovering texture patterns from original images without losing any details.

1.4 Research contribution

In this research paper I have shown an efficient moire effect removal method called DeepWPD. The main findings and outcomes of this paper are given below.

- My proposed DeepWPD network removes moiré patterns in both spatial and temporal domains by finding the frequencies of moire pattern in the affected image and eventually separating it from the original image.
- Although the focus of this research is mainly on removing moire artifacts from screen captured images I am hopeful that it will work successfully on non screen images too, where all the existing methods can not do. (Tested in a small number of non screen images

- This model first decomposes an image into 48 frequency bands or sub-bands. Then the sub-bands go through a Residual Dense Module Network and Dilation Convolution Network. Because of decomposing the image into a wide range of bands , detailed characteristics of the moire pattern can be extracted. Which can be a basis to create more advanced models for removing similar types of noise.

- Because of Residual Dense Module Network and Dilation Convolution Network the model preserves both high frequency and other low frequency components.

- The proposed DeepWPD architecture shows improved performance in the TIP2018 dataset, which is currently the biggest dataset of moire images according to my research.

1.5 Document Outline

The structure of my paper is as follows. The demoiréing can be categorized as one kind of image restoration in a complex case. So, in the Chapter 2 or literature review we covered different works done in this domain like Restoration based work, Textured specific restoration and lastly we discussed some deep learning based research works. In chapter 3 we discussed all the methodology of our proposed architecture, starting from decomposing the input image into sub-bands using Wavelet Packet Decomposition (WPT) following the Dilation Convolution Network(DCN) and Directional Residual Dense Network (DRDN). It is noted that the DCN and DRDN are separate neural networks working in parallel. Lastly, I gave a detailed overview of our DeepWPD architecture. Chapter 4 discusses my experimental set up and all about my training-testing dataset. Quality Evaluation Matrix is another major part of this chapter as I will compare the performance of my model with other models based on this evaluation matrix. For comparison and discussion in chapter 5 I used the evaluation matrix which was discussed in chapter 4 in detail. As with only some numbers it is difficult to understand the effectiveness of our model, I also gave a Visual Comparison by comparing the demoring result of sample images generated using my model to other state-of-the-art like CFNet , MuiltiscaleNet, Pix2pix and MobNet. Also, some results with my own screen capture moiré affected image are shown. In the end Chapter 6 concludes the effectiveness of my proposed model and how it can be improved further.

Chapter 2

Related Work

In this chapter, we will be discussing some work done by others in the field of image demoiring or related to demoiring.

2.1 Restoration based work

Image Demoiring can be categorized in different ways like color correction, texture removal, anti-aliasing etc. because of its complex nature. Work on removing moiré patterns is relatively new. One of the earliest works was done using convolutional neural networks for compression artifacts reduction[23][10]. They used Super-Resolution Convolutional Neural Network reducing different compression artifacts from an image. Some later research improved this model by increasing the network depth[27][12][21], by using ResNet like skip connections[9] and residual learning. Zhang et al.[25] replaced the RRCNN type connection in the memory block by a dense connection. According to the author, the most deep CNN super resolution model for image super-resolution (SR) can not make full use of the pyramid like features from the low quality images because of that they have relatively-low performance and their residual dense block based residual dense network gives better performance than other state-of-the-art methods.

2.2 Textured specific image demoiréing

As discussed before, fine patterns in an image can create different kinds of moiré artifacts. Most of the boundary detecting image decomposition methods assume that image detail is a relatively low difference variation. So, they apply filters that highlight features with increasing variation as following layers of detail elements. Because of that, such methods can not differentiate between high contrast and detailed features that needed to be intact. Using a local filter[5][11] is one of the best ways to remove these types of textures. Subr et al.[5] used local maxima of the input picture to extract the information about fluctuations. Fluctuations between local minima and maxima defines the detailed information. This method can distinguish between highly differing image textures and boundaries.

2.3 Image demoireing

The dataset we used for our training is from a paper from Sun et al.[24].They proposed a multiresolution fully connected convolutional neural network for removing moiré Patterns. In the initial stage, the input image is converted to multiple feature maps in different levels with different resolutions. The dataset they created has 130,307 pairs of images. This is currently the largest dataset with moiré pattern image. So, we naturally used this dataset to train our model, which is called TIP2018. Their model uses different kernels, slides and scale sizes for down sampling layers and up sampling layers. In this paper the proposed deep multiresolution network is compared to other denoising methods like RTV, SDF, IRCNN, DnCNN, VDSR, PyramidCNN, U-Net, V-Concate. None of these methods are specially designed for Image demoireing. In film to video transfer using telecine devices, Sidorov et al.[14] suppresses moiré patterns using a spectral method. Sur et al. developed a model to remove a more simple and regular type of noise called quasi-periodic noise. Wang et al.[26] proposed a framework called MopNet which makes use of property oriented learning for removing moiré patterns. To define the complex frequency of moiré patterns they used multiscale feature accumulation, followed by a channel wise target boundary predictor which exploits imbalanced magnitude among color channels and lastly to characterize the various appearance of moiré patterns they used a quality aware classifier. A two-step deep convolutional based neural networks model was proposed by Liu[22] for this particular task. It has two networks, a fine scale network and a coarse scale network. In the first step, the model takes an input RGB image, which is then down sampled. In the next step, it uses stacked residual blocks to remove the moiré patterns. In the last step to get the original resolution back, a fine scale network samples the demoiréd low resolution image.

Chapter 3

Methodology

In this chapter we will discuss each subnetwork inside our proposed DeepWPD architecture starting from how we implement Wavelet Packet Transform to decompose images to different su-bands following Dilation Convolution Network (DCN) and Directional Residual Dense Network(DRDN) for image demoiréing. Then we will give an overview of our complete DeepWPD architecture.

3.1 Wavelet Packet Transform(WPT)

We are using Wavelet Packet Transform (WPT) and choosen the Haar wavelet as the basis for the wavelet transform [7] to decompose our image into wavelet coefficients. In each level of WPT each image is decomposed into four sub bands or co-officiants which are horizontal , vertical, diagonal and detailed co-officiants. We used 2 level decomposition for our image. So, total 16 sub-bands or co-officiants will be produced. In figure 3.1(b) we can see an example of 2 level wavelet packet decomposition of the Lena image using Haar basis [7]. In figure 3.1(a) and 3.1(c), cA, cH, cV and cD represents Low frequency or Approximation Coefficients, High frequency coefficients or Horizontal Coefficients, Vertical Coefficients and Diagonal Coefficients respectively.

So, figure 3.2 shows what it looks like after applying the same 2 level WPT to a moiré affected gray level image from the TIP2018 dataset . Figure 3.2 (a) shows moiré free image or ground truth representation, (b) is the sub-bands of the same image with moiré patterns and (c)is the difference between a and b. Using the equation of sub-bands from [2], discrete wavelet transform (DWT) iteratively applies low-pass filter and high p-pass filter for computing the wavelet coefficients. Here, the value of low-pass filter is (1/2, 1/2) and the value of high-pass filter is (1/2, - 1/2). As we can see from figure 3.2(c) moire pattern is prominent in only certain subbands like cV1, cA3 and cV3.

Although we show only 16 sub-bands for a gray level image as our input of our model will be RGB images the number of sub-bands after wavelet transform will be $3\times16 = 48$. In the wavelet domain the height and width of the image is reduced to ¼ of the original size. 1×1 convolution is used to increase the 48 channels to 64 feature maps. So, the final dimension will be (64,64).

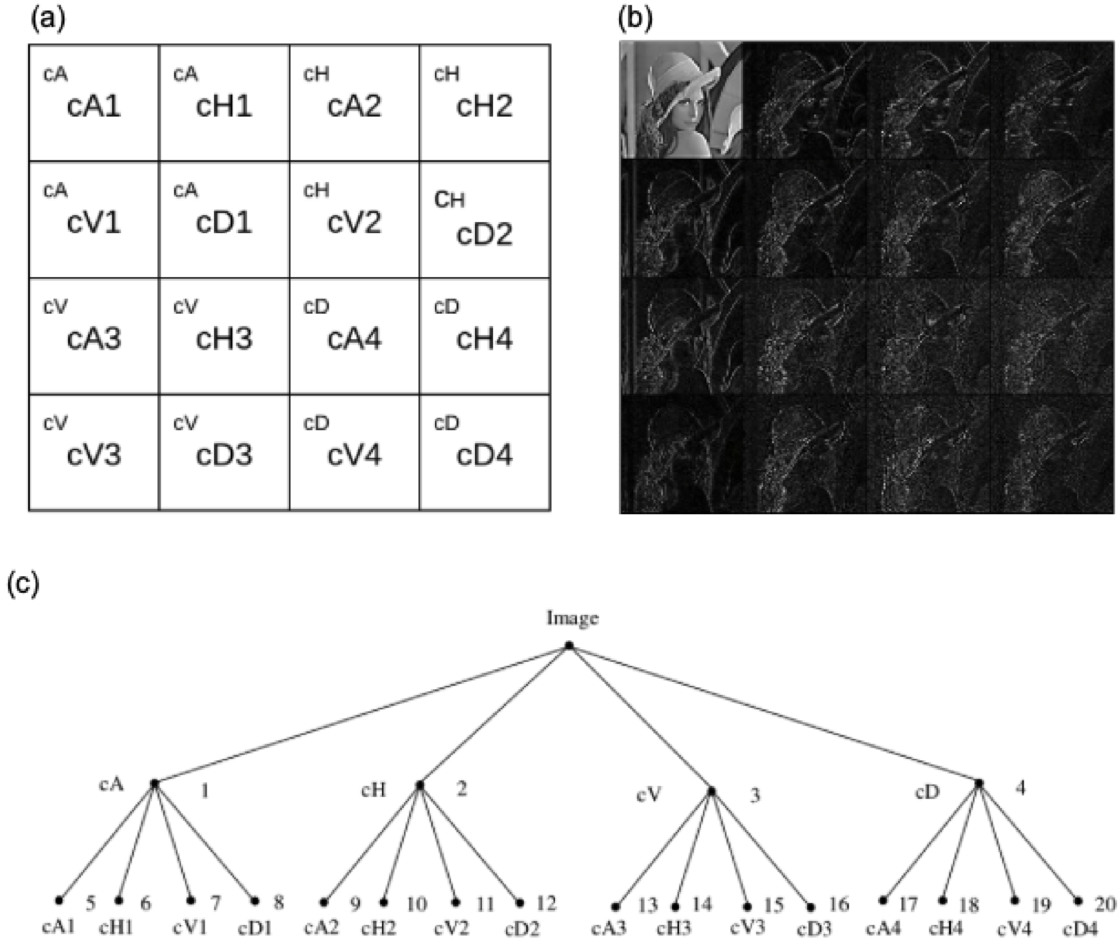

Figure 3.1: Discrete Wavelet Packet Transformation (DWPT). (a) Structure of a 2 Level wavelet packet decomposition using Haar basis, (b) 2 level wavelet packet decomposition of the Lena image using Haar basis, (c) 2–Level wavelet packet decomposition quad tree.

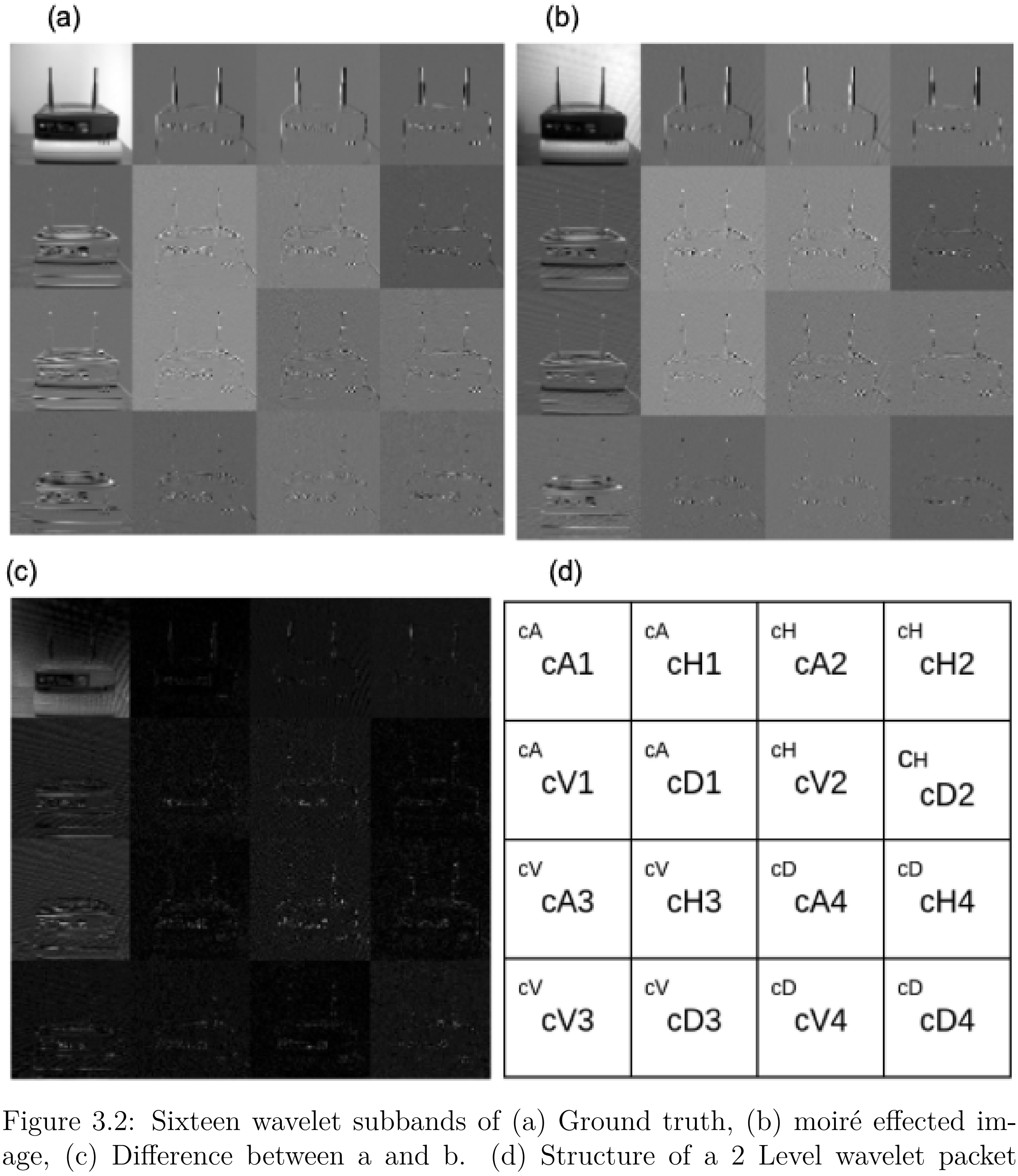

Figure 3.2: Sixteen wavelet subbands of (a) Ground truth, (b) moiré effected image, (c) Difference between a and b. (d) Structure of a 2 Level wavelet packet decomposition.

3.2 Dilation Convolution Network(DCN)

The Dilation Convolution Network contains two elements. A 3×3 dilated convolution layer followed by a 3×3 convolution layer as shown in figure 3.3. The dilated convolution layer overcomes the problem of losing details while pooling in convolution.

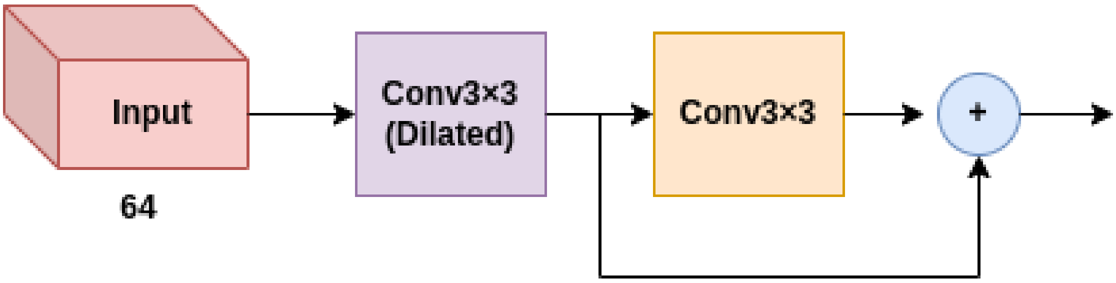

Figure 3.3: Dilation Convolution Network(DCN) architecture.

Dilated Convolutions are a type of convolution method that inserts gaps or skips pixels while taking pixels from the image where dilation will be applied. The mathematical formula of dilated convolution is[15]:

Let,

F : $Z^2 \rightarrow Rbeadiscretefunction.$
$\Omega_r = [-r, r]^2 \cap Z^2$
$k : \Omega_r \rightarrow R$
If a discrete filter of size $(2r + 1)^2$.

The discrete convolution operator * will be defined as:

$(F * k)(p) = \sum^{s+t=p} F(s)k(t)$

If l a dilation factor and $*_l$ will be:

$(F *_l k)(p) = \sum_{s+lt=p} F(s)k(t)$

But fixed size of dilation rate can create gridding problems[20] as illustrated in figure 3.4 . So, the seven dilation rate for our seven consecutive DCN is 1, 2, 3, 5, 8, 13, 21. The extra 3 × 3 convolution layer after the dilated convolution layer reduces the remaining gridding effect.

3.3 Directional Residual Dense Network (DRDN)

Directional Residual Dense Network (DRDN) as illustrated in figure 3.5 is responsible for finding high frequency moire patterns. Each DRDN contains two DRDN blocks .I used the Residual Dense Block (RDB) from "Residual Dense Network for

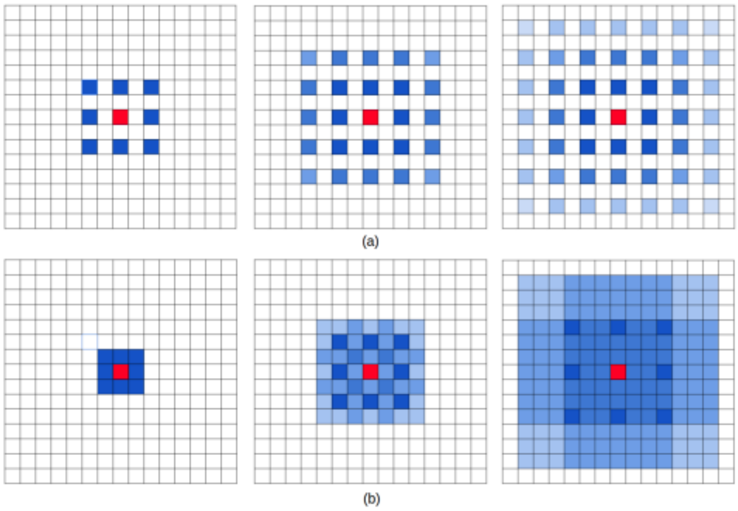

Figure 3.4: Different dilation rate to reduce gridding problems. From left to right: In the convolution layers with kernel size 3 × 3 the blue pixels do the convolution calculation of the center red pixel. (a) dilation rate is set to 2 for all convolutional layers. (b) taking dilation rates 1, 2 and 3 for subsequent convolutional layers.

Image Super-Resolution" [25] paper as my DRDN blocks. The original architecture is shown in figure 3.5.

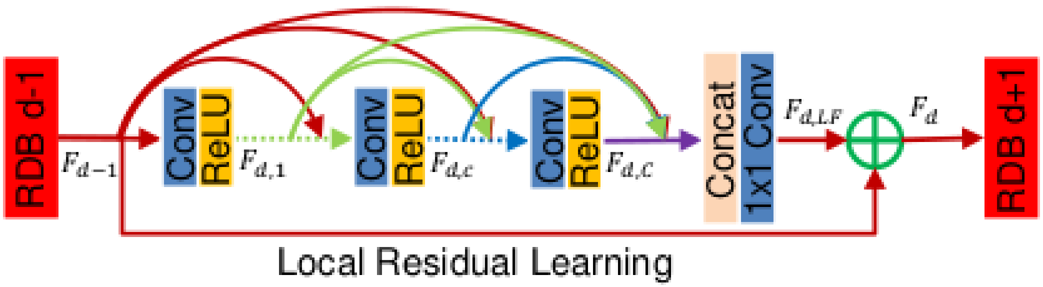

Figure 3.5: Residual dense block (RDB) architecture[25]

The densely connected convolutional layers of RDB blocks highlight the local features. In this design, there are direct connections from the current RDB to all the RDB, which ultimately gives the network a contiguous memory allocation. Because of the memory allocation technique, RDB effectively learns more features from all the local features from different layers. All this contributes to the stability of the training. Stochastic depth improves the training of deep residual networks because of skip connections similar to ResNets[17] in RDB. ResNets have achieved impressive performance by reducing the problem of vanishing gradient. ResNet uses a so-called "identity shortcut connection" or "skip connection" that skips one or more layers. The main goal of the residual network are:

- Identity mapping of ResNet prevents degradation of the accuracy and error rate in the deeper layers of the neural network

- To match the predicted with the ground truth, it keeps learning the residuals.

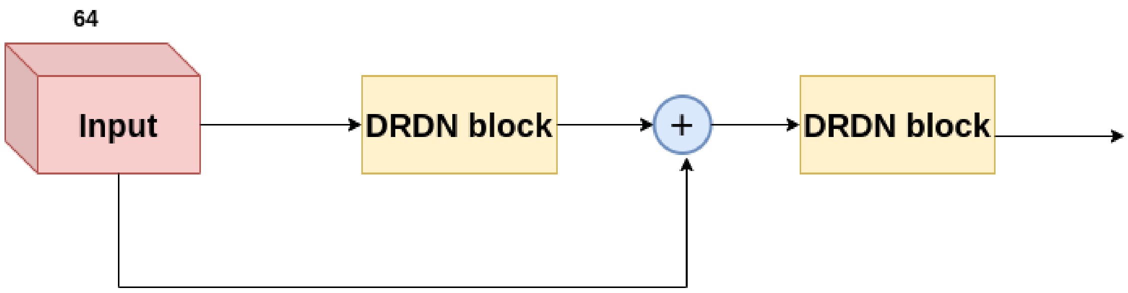

Figure 3.6: Directional Residual Dense Network (DRDN) architecture.

The output of the Directional block as well as each DRDN block are multiplied, weighted by , and then the result is summed with the input. Then the summed output is taken as an input for the second DRDN block. This architecture helps to find the positions of high frequency moiré patterns.

3.4 The combined DeepWPD architecture

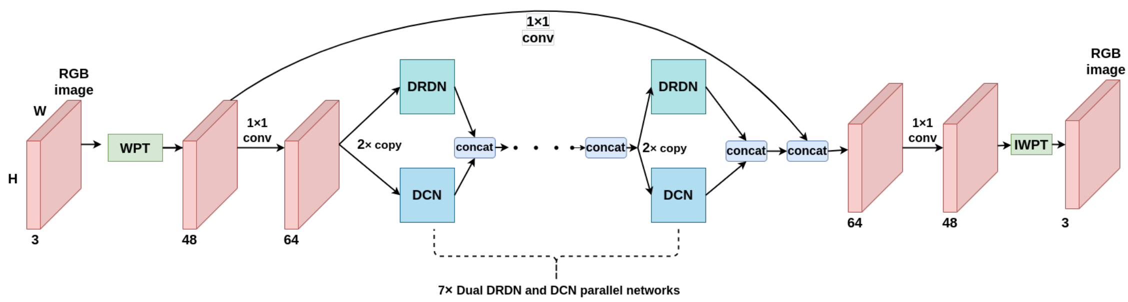

Figure 3.7: The proposed DeepWPD architecture.

There are 7 pairs of parallel networks. There are two networks in one pair, which are Dilation Convolution Network (DCN) and Directional Residual Dense Network(DRDN). The model takes an RGB image as an input. Wavelet Packet Transform converts them into 48 sub-bands, which is discussed in detail at chapter 3.1. These wavelet subbands extract all the information to recover the details feature for moiré pattern free images.
After 1×1 convolution, it creates 64 feature maps from 48 channels, and it is copied into two. One goes to DCN and another to DRDN as an input.
Dilated convolution or DCN is used to restore the information loss in detail because of pooling feature maps and Directional Residual Dense Network or DRDN finds the locations of high frequency moiré patterns in the image.
The final output of the 7x dual networks is a 64 channel feature map. 64 feature maps, again converted to 48 subbands using 1×1 convolution. Finally, an Inverse Wavelet Packet Transform(IWPT) converts the sub-bands into an output RGB image.

Chapter 4

Implementation

4.1 Data preparation

The largest benchmark right now with moiré pattern is TIP2018[24]. The benchmark contains 130,307 pairs of images. In each pair there is one image with moiré artifact and its corresponding noise free image or ground truth. The images used for creating this dataset are from ImageNet ISVRC 2012[4] dataset. From 130,307 pairs of images, 90% is used for training and 10% for testing. All the images in the TIP2018 dataset have a black border because black color is least affected by moiré artifacts. Every image is cropped to, 256×256 from the original resolution. Each image has 3 channels corresponding to RGB.

Figure 4.1: Some images from the TIP2018 dataset.

4.2 Experimental setup

We have fully implemented our proposed Deep learning based Wavelet Packet Decomposition using Pytorch on an NVIDIA GeForce RTX 3060 Ti 8 GB GPU. The entire dataset is divided into train and test. I used 1,18,456 images for training and 11,851 images for testing. The entire training process took 5 days on average. We use a batch size of 10. Initial learning rate is 0.0002. The value of is 0.2. Adam optimizer[8] is used to search the minimum of the loss function value. Adam optimizer is an efficient stochastic optimization which only requires first-order gradients, which consumes much less memory space. Adaptive Moment Estimation or Adam determines the adaptive learning rates for all the parameters of the optimization. It is the most used optimizer for deep learning based models because of its computational efficiency and less memory requirement.

4.3 Loss Function

The equation of total loss function of the network is given below
$\mathrm{L} = \mathrm{L}_1 + L_p + L_w$

L_1 = smooth l1 loss between the image and its ground-truth in the RGB Domain
Equation of L1loss:

L_1=$\{1/2$*$\mathrm{a}^2 for|a| <= 1, \delta(a - 1/2) otherwise\}$

Here,
$a = y - \hat{y}$

y=true label

$\hat{y}$=predicted label

δ=hyperparameter to control the smoothness of the loss function

$\mathrm{L}_p = perceptualloss[19]$

$\mathrm{L}_w = waveletloss = l_{MSE} + l_{detail}$

$\mathrm{l}_{MSE} = Y_1 \sum_{i=1}^{3} |\hat{c}_i - c_i| + Y_2 \sum_{i=4}^{N} |\hat{c}_i - c_i|^2$

$\mathrm{l}_{detail} = \sum_{i=4}^{N} max \left(\alpha |c_i|^2 - |\hat{c}_i|, 0\right)$

Here,
$c_i = i_t h$ ground truth
$\hat{c}_i = i_t h$ sub band

4.4 Quality Evaluation Matrix

To make comparisons with other state-of-the-art models, we used the widely used metric for image quality evaluation called PSNR and SSIM.

Peak signal to noise(PSNR)[3] measured in dB,
PSNR = $10.\log_{10}\left(MAX_l^2/MSE\right)$

Structural similarity index measure (SSIM)[6],
SSIM(x,y) = $((2\mu_x\mu_y + c1) + (2\sigma_{xy} + c_2))/((\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2))$

Here,
x = the pixel sample mean of x
y = the pixel sample mean of y
σ_x^2 = the variance of x
σ_y^2 = the variance of y
$\sigma_x y$ = the covariance of x and y
$c_1 = (k_1L)^2, c_2 = (k_2L)^2$ two variables to stabilize the division with weak denominator
L = the dynamic range of the pixel-values
k_1 = 0.01
$k_2 = 0.03$

4.5 State of the art methods

We compared the result of our method against the state of the art methods related to Moiré Photo Restoration. Most recent work in this field is MopNet [26] which was done in 2019. Other state of the art methods are CFNet [22] , MuiltiscaleNet [24] and Pix2pix [18] . To make the comparison reliable, I trained on the widely used TIP2018 data set, using the settings from [24].

Chapter 5

Comparison and discussion

5.1 Quantitative evaluation

We used PSNR and SSIM as our Evaluation Matrix which is discussed in chapter 4.3. Quantitative similarity between our DeepWPD and other state of the art methods is shown in Table 5.1.

Table 5.1: Quantitative Comparison Table

	Pix2pix	**MuiltiscaleNet**	**CFNet**	**MopNet**	**DeepWPD**
PSNR mean(dB)	25.32	26.11	25.52	26.8	27.50
PSNR gain	2.18	1.3	1.98	0.7	0
SSIM mean	0.756	0.801	0.810	0.895	0.904
SSIM gain	0.148	0.103	0.094	0.046	0

Among the state of the art image demoiring methods MopNet is most effective and recent for removing moiré patterns. As we can see from table 5.1 our DeepWPD model outperformed the existing state of the art MopNet by 0.7dB gain in PSNR and 0.046 increase in SSIM value. In comparison to other methods like Pix2pix, MuiltiscaleNet and CFNet the gain of our DeepWPD is 2.18dB, 1.3dB9, 1.98dB for PSNR and 0.148, 0.103, 0.094 for SSIM.

5.2 Visual result of demoiréing using DeepWPD

Figure 5.1 shows some demoiréing results using our DeepWPD model. All these images are from test data of TIP2018 dataset.

Figure 5.1: Output result of the proposed DeepWPD demoiréing algorithm on some camera captured screen images from TIP2018.

5.3 Result of colored moiré artifacts

We further experimented with texture like images separately, and it can be seen in figure 5.2 that our DeepWPD is really effective to erase colored moiré patterns without distorting the color or pattern of the underlying image. It is noted that almost all the training images contain a screen captured image, and very few of them have this colored moiré artifacts. It shows the potential of our DeepWPD model of removing diverse moiré patterns.

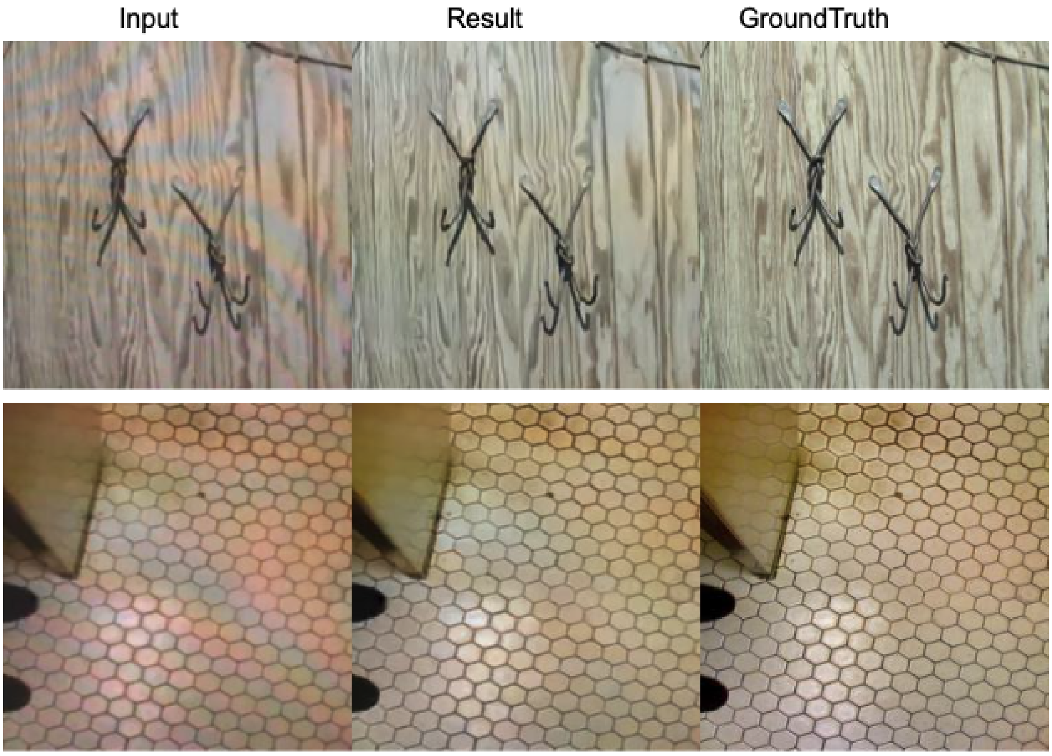

Figure 5.2: Removing colored moiré artifacts from texture images using DeepWPD.

5.4 Testing demoiréing with our own captured images

I also tested our trained model with our own screen captured moiré affected images. The image was captured with the 13 MP, f/2.0 camera of Motorola Moto G3 phone. The monitor was a SAMSUNG LF22T350 22 inch 1920 x 1080 IPS LED Monitor. Sample results are shown in figure 5.3.

Figure 5.3: Restoration of screen captured moiré photos taken with Motorola Moto G3

Chapter 6

Conclusion and Future work

There are a very limited number of image data sets with moiré artifacts. We are planning to build our own dataset with more scenarios. The TIP2018 dataset is mainly of screen capture moiré affected images. Although our proposed model successfully removes both screen capture and non-screen capture images, there is no dataset dedicated for only non-screen capture moiré affected images. We will create a dataset with different pattern and architecture images with high frequency pattern where there is a possibility of moiré affected even if it is not screen captured. According to our assumption, our method has the potential to Deraining and Deraindrop any images taken on a rainy day. But more experiments are needed for exploring this domain.

In some images we saw Moiré artifacts distorting the color, which might be an experiment for our future work. Another drawback of our DeepWPD model is that it could not clearly reduce blurriness of the input images. The author of MopNet[26] experimented with a color distorted Moiré affected image and demoiréd it with their trained model, which clearly failed.

I are planning to implement a directive recurrent neural network by modifying the existing IRNN[16]. This approach may give my network the ability to detect moiré patterns of different slopes and highlight moiré patterns in spatial distributions by generating the attention map.

I observed that rain streaks create the same type of effect in images like moiré artifacts. According to my research, images taken on a rainy day or having any kind of water drop can not be de-noised using traditional image denoising methods. So, there is a potential for our model to be used in that domain also. But no particular dataset is found. But a dataset with a rainy effect can be made in a controlled environment. So, our model holds the potential to be used in different domains.

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