Demoiréing for Screen-shot Images with Multi-channel Layer Decomposition

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***Abstract*—Moiré patterns on screen-shot images are mainly due to the aliasing of the grid of the display and the camera sensor, which heavily degenerated the image quality. This paper proposes an demoiréing method for screen-shot images via *layer decomposition on polyphase components* (LDPC). The layer decomposition model separates the image into a background layer and a moiré layer, which are both regularized by a patch-based Gaussian Mixture Model (GMM) prior. To enhance the distinguishability between the image patches and moiré patches, the input image is first subsampled into four polyphase components, each of which is decomposed with the GMM-based layer decomposition model. The proposed model is applied on luminance (Y) channel to weaken the intensity of moiré patterns, and on red, green, blue channels respectively to further remove moiré patterns. Experimental results demonstrate that the proposed method is able to efficiently remove moiré artifacts for screen-shot images and outperform several other methods.**

***Index Terms*—Moiré patterns, layer decomposition, polyphase components, patch-based prior, screen-shot images**

I. Introduction

Moiré patterns are due to the interference between overlapping grid, lines or patterns. Specially moiré patterns on screen-shot images, which heavily degenerated the image quality, are mainly generated by two aspects. One is the aliasing of the grid of the display and the camera sensor; the other is re-sampling of images [1]. Due to the similar statistical distribution of moiré patterns and context information, it is challenging to remove the moiré while maintaining the image details and edges. Fig. 1 shows the moiré artifacts on a screen-shot image and a image removing moiré patterns via our method.

There mainly exists two kinds of approaches to suppress moiré artifacts. One is pre-processing, which is placing an optical low-pass filter in front of the lens avoiding aliasing [2]. However, it cannot completely eliminate moiré artifacts while reserving the image details. Similarly, it is time-consuming to capture a moiré-free image by selecting an optimal angle of the lens [3] [4].

The other approach is post-processing. To our best knowledge, there is not existing methods addressing demoiréing of screen-shot images. Most advanced filters [5] fail to effectively remove moiré artifacts from screen-shot images. Closed related work include moiré suppression for scan images [6] [7]

(a) (b)

Fig. 1. (*a*) Input image with moiré artifacts; (*b*) Image demoiréd by our method.

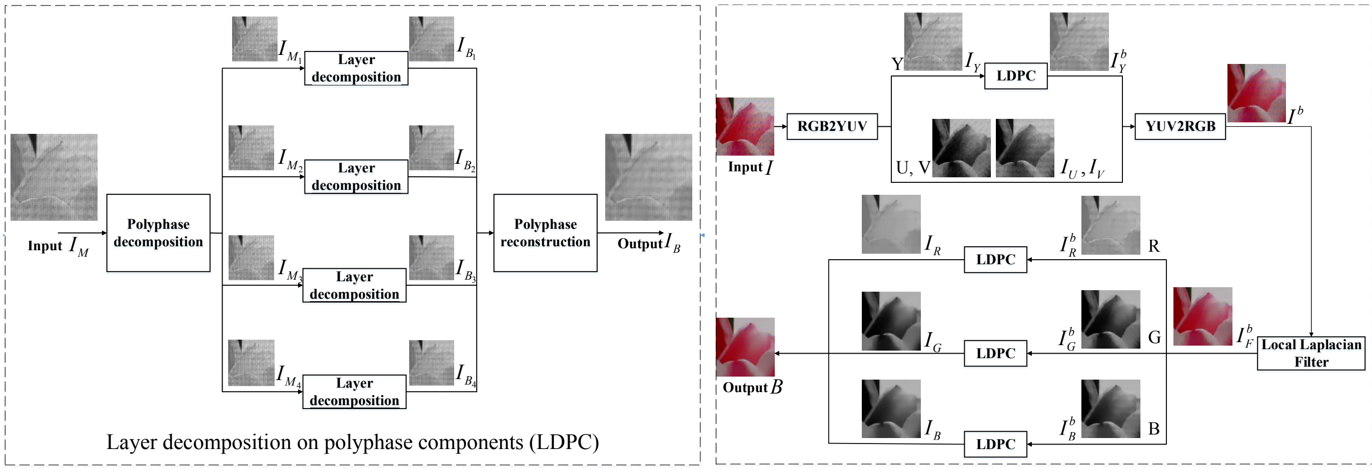
and texture images [8]. However, these methods can not well handle moiré patterns in screen shot image. Similar with moiré patterns, the removal of canvas patterns is also a related problem. Cornelis *et al.* in [9] propose a source separation method to suppress the canvas components in digital acquisitions of paintings. It is also possible to use Adobe Photoshop to remove moiré patterns [10], nevertheless the quality of results mainly depend on the skill of users and the distribution of moiré patterns.

In this paper, we propose a *layer decomposition on polyphase components* (LDPC) model to separate the screen-shot images into a background layer and a moiré layer. The polyphase decomposition is applied on the input image to obtain four subsampled images. The layer decomposition based on patch-based priors separates each subampled image into a background layer and a moiré layer. Patch-based priors based on Gaussian mixture models (GMMs) [11] [12] are used on both layers. For demoiréing of the input image, we firstly apply the proposed model on luminance (Y) channel to weaken moiré patterns. Then, we use a local laplacian filter inspired by [13] to further smooth moiré patterns, and maintain details of image. Finally the proposed model is applied again on red, green and blue channels respectively to further remove moiré artifacts. Experiments evaluated on screen-shot images show that the proposed method outperforms several methods in terms of visual performance.

II. Proposed Method

A. Framework

The framework of proposed demoiréing model is demonstrated in Fig. 2. The input image I_M, as shown in Fig. 2(a), is firstly decomposed into four subsampled images



(a) (b)

Fig. 2. (a) The proposed LDPC model. (b) The framework of our proposed screen-shot images demoiréing method. Luminance (Y) and chrominance (U,V) channels of the input image I are denoted as I_Y, I_U and I_V, respectively. I_R^b, I_G^b and I_B^b represent the red, green and blue channels of the filtered image I_F^b. I_R^b, I_G^b and I_B^b are processed by LDPC model, generating I_R, I_G and I_B respectively.

I_{M_i}, $i \in (1,2,3,4)$. Afterwards, each subsampled image is decomposed into moiré layer I_P^i and background layer I_B^i, $i \in (1,2,3,4)$ using the layer decomposition model based on GMM priors. The background layer I_B is integrated by the subsampled images I_B^i. The above two steps are termed as a *layer decomposition on polyphase components* (LDPC) model.

As for a degraded image I in Fig. 2(b), we firstly apply the LDPC model on the Y channel to weaken the enormous energy of irregular color strips of moiré patterns. Afterwards, the generated background layer I_Y^b is converted back to the RGB space I^b to filter out undesired strips. The local laplacian filter [13] is adopted to smooth out the moiré patterns while preserving image details and edges. To further remove the remaining moiré patterns, the LDPC model is applied again on red, green and blue channels of the filtered image I_F^b respectively, generating our desired clean image B.

B. Polyphase Decomposition on Screen-shot Images

Since the high-level similarity between the natural image and color strips of moiré artifacts, the recovered images could still preserve the residual color strips. This makes the polyphase decomposition step a vitally effective means in the proposed method. Note that moire patterns are generally s-mooth, which is difficult to distinguish from smooth structures in images particularly with generic image priors. We observed that the structures of moire patterns could be significantly changed in subsampled images. Therefore, we first decompose the input image into four polyphase components, on which the layer decomposition is applied for demoiréing. Specifically, it decomposes the input image into four subsampled images at $2\times$ down-sampling rate to disturb the feature of moiré patterns while nearly preserving the feature of natural images. Then, the following step, layer decomposition, can correctly distinguish the context information from moiré patterns.

C. Layer Decomposition Model with Patch Priors

The screen shot image I can be regarded as the superimposition of the background layer B, the moiré patterns layer M and Gaussian noise n with variance σ^2, assuming the following additive model:

$$I = B + M + n. \tag{1}$$

However, inferring B and M from I is ill-posed. So we introduce two priors for the background layer and the moiré layer for regularization. The problem can be formulated into the following minimization:

$$\min_{B,M} \ \frac{1}{\sigma^2}\|I - B - M\|_2^2 + \phi(B) + \psi(M), \tag{2}$$

where $\|I - B - M\|_2^2$ is the fidelity term. $\phi(B)$ and $\psi(M)$ will defined two priors and other constraint terms to regularize inference.

Firstly, $\phi(B)$ is wrote as following:

$$\phi(B) = -\sum_i \log \rho_b(P_i B) + \alpha\|\nabla B\|_1, \tag{3}$$

where $\rho_b(P_i B) = \sum_{k=1}^{K} \pi_k N(P_i B|\mu_k^{(b)}, \Sigma_k^{(b)})$, and P_i is an operator to extract the i-th patch and reshape it into a vector. The size of patch is 8×8. K is the number of mixture Gaussian components, π_k is the mixture weight, and $\mu_k^{(b)}$ and $\Sigma_k^{(b)}$ denote the mean and covariance matrix for the k-th component respectively. We use the pre-trained GMM model in [11], which contains 200 mixture components with zero-mean. Since natural images has sparse gradient, we use $\|\nabla B\|_1$ to encourage the smoothness of natural image, where ∇ denotes the gradient operator and $\|\cdot\|_1$ represents the ℓ_1 norm. α is set to 0.025.

Similarly, we impose on the priors of the moiré layer as following:

$$\psi(M) = -\sum_i \log \rho_m(P_i M), \tag{4}$$

where $\rho_m(P_i M) = \sum_{k=1}^{K} \pi_k N(P_i M|\mu_k^{(m)}, \Sigma_k^{(m)})$. $\rho_m(\cdot)$ is trained by the patches of images with only moiré patterns.

The minimization (2) is non-convex, due to the patch-based GMM priors. We apply half-quadratic splitting [11], obtaining the following optimization:

$$\begin{aligned}\min_{B,M}\ & \frac{1}{\sigma^2}\| I-B-M\|_2^2+\frac{\beta}{2}\|\nabla B-D\|_2^2+\alpha\|D\|_1\\ &+\frac{\beta}{2}\sum\nolimits_i(\|P_iB-\varrho_{b_i}\|_2^2+\|P_iM-\varrho_{m_i}\|_2^2)\\ &-\sum\nolimits_i\log\rho_b(\varrho_{b_i})-\sum\nolimits_i\log\rho_m(\varrho_{m_i})\\ &\text{s.t.}\quad 0\le B,M\le 1,\end{aligned}\tag{5}$$

where D, ϱ_{b_i} and ϱ_{m_i} are substitute variables of ∇B, P_iB and P_iM, respectively. β is a positive parameter starting from 200 and is doubled in each iteration. We set $\sigma=5\times10^{-3}$. Eq. (5) is optimized by solving the following three subproblems, alternately.

(1) D - subproblem: D is optimized by the following formulation, ignoring irrelevant terms:

$$D^{(k+1)}=\arg\min_D\alpha\|D\|_1+\frac{\beta}{2}\|D-\nabla B^{(k)}\|,\tag{6}$$

which have a closed solution of shrinkage:

$$D^{(k+1)}=\text{soft}(\nabla B^{(k)},\frac{\alpha}{\beta}),\tag{7}$$

where $\text{soft}(x,\mu)=\text{sign}(x)\max(|x|-\mu,0)$ is the shrinkage operator on x with a threshold μ.

(2) $\{B,M\}$ - subproblem: we use the constrained L-BFGS [12] [14] to solve the following $\{B,M\}$ - subproblem:

$$\begin{aligned}\{B^{(k+1)},M^{(k+1)}\}&=\arg\min_{B,M}\frac{1}{\sigma^2}\| I-B-M\|_2^2\\ &+\frac{\beta}{2}\sum\nolimits_i(\|P_iB-\varrho_{b_i}^{(k)}\|_2^2+\| P_iM-\varrho_{m_i}^{(k)}\|_2^2)\\ &+\frac{\beta}{2}\|\nabla B-D^{(k+1)}\|_2^2\quad\text{s.t. } 0\le B,M\le 1.\end{aligned}\tag{8}$$

(3) ϱ_{b_i}, ϱ_{m_i} - subproblem: the optimization with respect to ϱ_{b_i} and ϱ_{m_i} are arranged as:

$$\begin{aligned}\varrho_{b_i}^{(k+1)}&=\arg\min_{\varrho_{b_i}}\frac{\beta}{2}\| P_iB^{(k+1)}-\varrho_{b_i}\|_2^2-\log\rho_b(\varrho_{b_i})\\ \varrho_{m_i}^{(k+1)}&=\arg\min_{\varrho_{m_i}}\frac{\beta}{2}\|P_iM^{(k+1)}-\varrho_{m_i}\|_2^2-\log\rho_m(\varrho_{m_i}).\end{aligned}\tag{9}$$

In this way, ϱ_{b_i} and ϱ_{m_i} for each patch can be updated in parallel. The approximate MAP estimation suggested in [11] is applied to update ϱ_{b_i} and ϱ_{m_i}. Calculating the likelihood of every component of each patch in GMM model, we select the component with the largest likelihood. Then we apply a Winer filter on that component and obtain updated ϱ_{b_i} and ϱ_{m_i}.

D. Local Laplacian Filter

The local laplacian filter [13] is adopted to smooth moiré patterns and enhance image details. We build a Gaussian pyramid and point-wisely manipulate each scale to generate the subband of the associate Laplacian pyramid. For each coefficient g at a particular Gaussian pyramid scale l, a sub-region Ω is extracted and pixels in Ω are to suppress moiré artifacts. Let p be a pixel in Ω and $\tilde{p}$ be the modified vision of p defined by:

$$\tilde{p}=\begin{cases} g+f(p;g,\sigma_m,\gamma_m), & |\,p-g\,|<\sigma_m, \quad (10a)\\ g+f(p;g,\sigma_d,\gamma_d), & \sigma_m<|\,p-g\,|<\sigma_d, (10b)\end{cases}$$

where $f(p;g,\sigma,\gamma)=\text{sign}(p-g)\sigma f(\frac{|p-g|}{\sigma})$ is a normalized variation of p with respect to g. The parameter σ_d distinguishes image details from edges and parameter σ_m is used to further distinguish moiré patterns from image details. $(\Delta)^\gamma$ is a smooth function, where $\gamma\ge 0$ is a user-defined parameter. The value is set to be larger than 1 to achieve smoothness, otherwise to achieve enhancement. Image pixels are considered as moiré patterns when $|\,p-g\,|<\sigma_m$, and we set $\gamma=1.5$. Otherwise, image pixels are considered as image details, when $\sigma_m<|\,p-g\,|<\sigma_d$, and we set $\gamma=0.9$. σ_m and σ_d are set to 0.09 and 0.4, respectively.

The modified sub-region is transformed into a Laplacian pyramid, then the corresponding Laplacian coefficient of g is copied into the associated pyramid at the same location and scale. After processing all coefficients, the desired image is reconstructed from the generated Laplacian pyramid.

III. Experimental Results

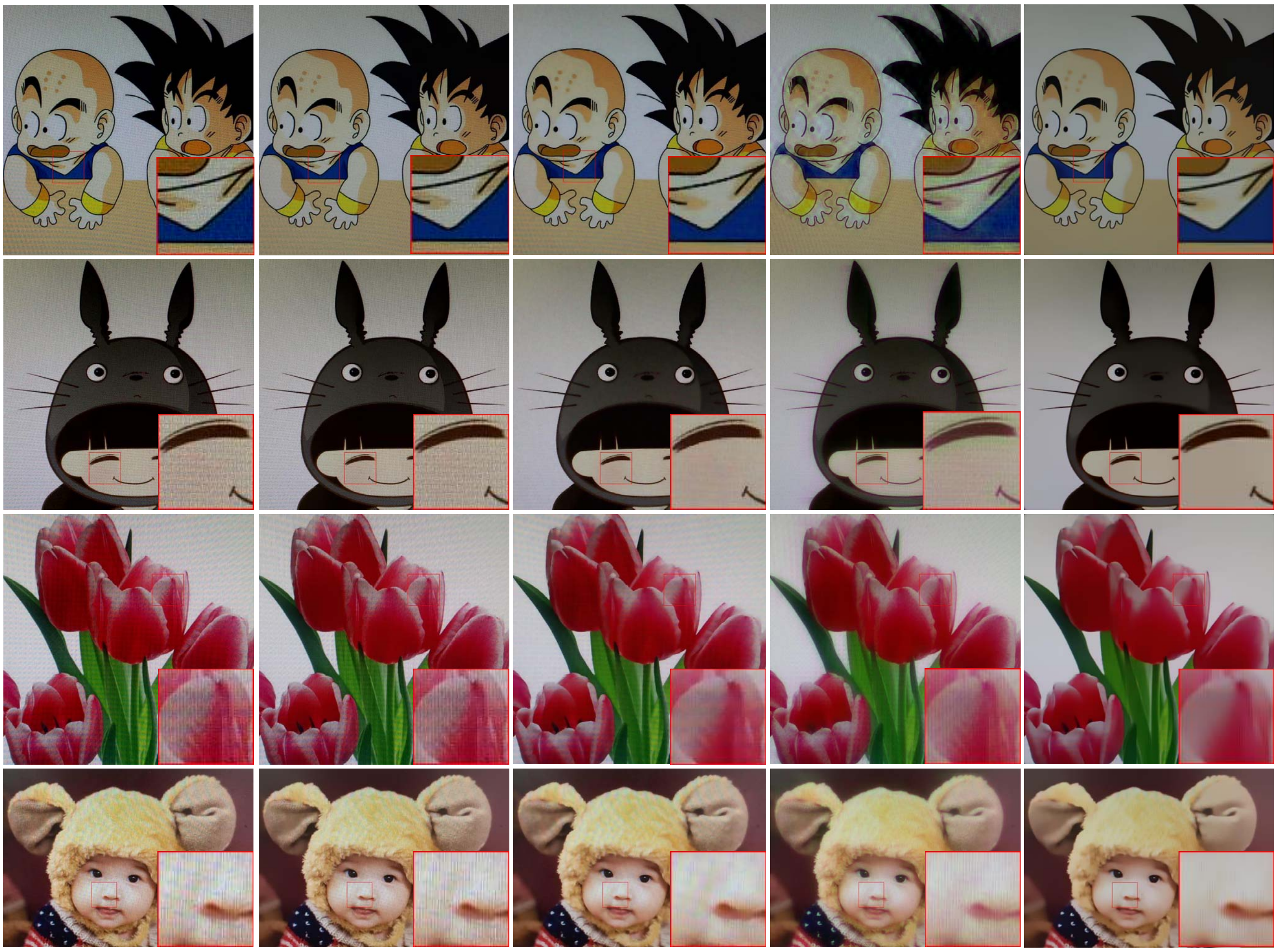
To our best knowledge, there is no approach to address screen-shot images demoiréing. Three methods are chosen for comparison, including local laplacian filter (LLF) [13], bilateral filter (BF), and a signal decomposition and guided filtering model [8] (SDGF). Experimental results are demonstrated in Fig. 3. To show the detail of results, we extract a magnified region marked by red rectangle.

As shown in Fig. 3(b), for each image, LLF can only smooth the color strips of moiré patterns. This suggests that a single local laplacian filter is insufficient for remove moiré patterns on screen-shot images. The bilateral filter generate acceptable results as shown in Fig. 3(c). Moiré patterns are partially removed. However, when the moiré patterns are wide and strong strips, the filter keeps them as edges. The SDGF method in [8] can better remove the color strips, because demoiréing on clothes mainly focus on removing the moiré strips. However, it can not recognize other types of moiré artifacts and even preserves them as image textures. Meanwhile, results in Fig. 3(d) show the presence of block artifacts and pseudo colors around edges. SDGF also changes on the tone of whole images.

Fig. 3(e) shows that, the proposed method efficiently remove moiré patterns on screen-shot images while intelligently preserving image details and edges. Furthermore, our method is capable of removing different kinds of moiré patterns by utilizing the patch-based priors on layer decomposition imposed on subsampled images. Our method produces the best results of demoiréing in visual quality.

IV. Conclusion

This paper proposes a layer decomposition demoiréing model on subsampled screen-shot images based on patch-based priors pre-trained by natural images and moiré patterns. We apply the model on Y and RGB channels respectively to better remove the moiré patterns and produce more efficient results. Experimental results show that the proposed method could



(a) (b) (c) (d) (e)

Fig. 3. Result images used in our experiments. (*a*) screen-shot images with moiré artifacts, (*b*) LLF results, (*c*) BF results, (*d*) SDGF results, (*e*) our results.

largely remove the moiré patterns while preserving image details. However, in some cases, our method may inevitably cause the blur of image details and cannot completely suppress some over wide color strips. In the future, to promote our results, we would like to explore the distribution law of moiré patterns in screen-shot images and improve the ability of filter since the applied filter is possible to smooth image details. Furthermore, we could give out quantitative results based on screen-shot images comparing with ground truth.

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