Microscopic Muscle Image Enhancement

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Abstract—We propose a robust image enhancement algorithm dedicated for muscle fiber specimen images captured by optical microscopes. Blur or out of focus problems are prevalent in muscle images during the image acquisition stage. Traditional image deconvolution methods do not work since they assume the blur kernels are known and also produce ring artifacts. We provide a compact framework which involves a novel spatially non-uniform blind deblurring approach specialized to muscle images which automatically detects and alleviates degraded regions. Ring artifacts problems are addressed and a kernel propagation strategy is proposed to speedup the algorithm and deals with the high non-uniformity of the blur kernels on muscle images. Experiments show that the proposed framework performs well on muscle images taken with modern advanced optical microscopes. Our framework is free of laborious parameter settings and is computationally efficient.

Index Terms—Muscle Image, Computer Aided Diagnosis, Microscopic Image, Medical Image Enhancement, Image Deblur.

I. INTRODUCTION

SKELETAL muscle is an extremely adaptive tissue that is able to change size depending upon external stimuli. Increases in muscle mass in response to resistance training and losses in mass caused by disuse or associated with chronic diseases such as cancer and HIV are primarily due to hypertrophy or atrophy of individual muscle fibers, respectively, rather than addition or loss of fibers [1]. Thus, The ability to accurately and efficiently quantify the morphological characteristics of muscle cells, such as cross-sectional areas (CSAs), is vital for assessing muscle function, since muscle mass is the primary determinant of muscle strength [2], [3]. One example is the Idiopathic Inflammatory Myopathy (IIM) detection, which is characterized by weakness and inflammation of skeletal muscles [4]. A very important prerequisite for accurate CSA quantification is the high-quality microscopic image acquisition, after the muscle specimen is stained with H&E or fluorescence.

Unfortunately, the non-flat surface of muscle specimens, which involves massive tissue protuberances and concavities, impedes the users holding the desired observatory regions to uniformly fall into the focus plane of the microscope. Nevertheless, modern advanced optical microscopes for fluorescence or H&E specimens often involve a lot of laborious manual configurations of confusing parameters. It is usually a prerequisite for the users to be well trained and extensively practiced in order to properly adjust those settings. Thus, improper or even erroneous settings of parameters are inevitable. Blur/defocus is consequently produced occasionally at some regions, or the entire scope of the captured muscle microscopic images.

Vagueness and ambiguity are observed on these regions not only degrading the visual quality but also hindering the success of the subsequent computer aided diagnosis operations potentially included in an automatic diagnosis system such as segmentation of cells and the detection of a certain disease.

In this work, we propose a compact framework to enhance the visual quality of the poorly captured muscle images. The proposed framework involves the following steps: 1) Local blur/defocus kernel estimation. A group of spatially variant blur kernels for part of the muscle image are estimated based on the gradient information under carefully chosen constraints and priors. 2) Kernel propagation. The estimated kernels are propagated to their neighborhood and speedup their kernel estimation. 3) Non-blind image enhancement. An efficient image deconvolution algorithm involving the most recent findings in image statistics is performed locally based on the estimated kernels. Fast convergence speed is achieved. The proposed method has an automatic design that reduces blur and out of focus in a one-click style. The users are thus liberated from laborious parameter tweaks.

We do not confine the type of the degradation as specific defocus caused by the limited or misplaced depth of field (DoF) produced by the optical system of the microscope. Rather, we put it into a more general blur model that captures the local linear transforms represented as a (or a group of)
freely shaped kernel to cope with the degradation caused by sophisticated blur such as lens aberration [5]. The proposed muscle image enhancement is characterized as blind, non-uniform blur kernel estimation and deconvolution with the purposes of both computational efficiency and automation. Conventional methods, such as as Weiner filters [6] and Richard-Lucy deconvolution [7], are parametric since they assume the precise blur kernels are known. In addition, the enhanced images provided by them are often less constrained and thus have strong artifacts. The natural image defocus removal methods such as [8] usually rely on a robust map estimation of Gaussian parameter and the existence of similar patch pairs between the blurry and the good regions. In contrast, the proposed method utilizes the sparsity of the gradient as clue to guide the algorithm automatically produce good quality results. No heuristic computations are involved and the noise is also addressed with proper models. The enhancement framework is thus both robust and automatic.

The blur kernel estimation step involved in the proposed framework differs from the existing non-uniform methods in literature significantly. Those works are dedicated to model the spatial motion of a hand-held camera. 3D translations, in-plane and/or out-of-plane rotations are involved and are estimated during the energy optimization stage. However, rotations do not happen on a microscopic muscle image. What is more important is that the blur happened in microscopic muscle images is much different from typical natural image blur, exhibiting much more severe spatial variances but less (still exists though) directional blur. Although part of the blur can be understood as out of focus and is proper to be modeled using an exponential family function (such as Gaussian or Poisson), putting such rigid constraints does not perform well for lack of flexibility, especially on muscle images with strong spatial variance. We address this problem by proposing a new spatially variant kernel estimation algorithm. Specifically, a group of spatially invariant kernels are estimated for some randomly chosen local image regions. These estimations are propagated to their neighboring regions serving as initiations of their optimization arguments. This step not only preserves the coherence of the inter-region image structures but also accelerates the computational efficiency drastically. Although we also encourage the estimated kernels to be Gaussian-shaped, the weight assigned to this prior is gradually deducted during the iteration of the algorithm. This brings the benefit that the blur is treated as defocus problem at the first few iterations to produce a reasonable intermediate result. The most recent findings in image statistics suggesting the sparsity constraint on gradient of the image are utilized during the kernel estimation. An efficient deconvolution method is used to recover the blurred muscle images after all kernels are estimated.

Although the proposed method can effectively remove the blur and defocus, the recovery of some regions that are severely blurred or defocused cannot rely on only local neighbor-bored pixel information that typical deblur methods utilize since the original image information is mostly lost. We propose to use a patch synthesis algorithm to address this problem. These severely blurred regions are detected via a simple gradient computation after the muscle image is processed via the proposed spatially non-uniform deblur algorithm. Then, a fast non-local similar patch search is used to find out candidates of synthesis for the detected regions. Candidates with both high similarity and good patch-wise coherence preservation are selected and replace the highly degraded patches. Finally, a smoothing algorithm is performed to remove the artifacts produced by during the synthesis step.

Extensive experiments are conducted on muscle images captured with advanced optical microscopes where both mild and severe blur happen. We use an Olympus VS 120 advanced optical microscope dedicated to medical specimen observation and capture 44 muscle images. Most images more or less contain some regions showing blur or defocus problems. One example of the enhancement provided by our framework is shown in Figure 1. The users are free of empirically choosing parameters for our algorithm since the framework is completely automatic. The processing time for each three color channel muscle image ranges from two minutes to eleven minutes, depending on the resolution which is normally more than 10m pixels. Results show that the proposed framework is both effective and computationally efficient.

The remaining of this paper is organized as follows: We briefly survey relevant works in the current literature for the proposed framework in section II. The proposed muscle image enhancement framework is introduced in details in section III. We present the experimental results in section IV. We conclude our paper and give a discussion on the future work in section V.

II. RELATED WORK

The most relevant works to the proposed muscle image enhancement framework can be categorized as the single image blind deconvolution. The problem is typically modeled as a blur kernel (or point spread function (PSF)) convolves with the latent, distortion free image. The blur kernel can be a Gaussian-shaped distribution to model out of focus (defocus), or a motion trajectory to model the blur caused by spatial shifts of a camera during a long time exposure. Blind image deconvolution is considered as extremely difficult due to its severe ill-posedness since both the latent image and the blur kernel are assumed unknown. Traditional methods such as Weiner filters [6] and Richard-Lucy deconvolution [7] are popular due to their simplicity and efficiency. However, these methods cannot work on blind image deconvolution since they assume the blur kernel to the latent image is known. In addition, these works produce large amount of undesired ring-like artifacts during the latent image recovery, even if we assume the kernel is available (hand-designed model with super-tweaked parameters). In the past decade, there has been a significant progress on the blind image deconvolution involving both the phases of blur kernel estimation and latent image recovery. Various constraints are designed on both the latent image and the blur kernel with much more improved results being obtained. The reason of their success is twofold: 1) The constraints made on the kernel and the latent image alleviate the ill-posedness of the blind image deconvolution
problem. 2) Well designed constraints can effectively suppress the artifacts on the latent image and exclude those unnatural latent images from the solution space. Noise in the estimated blur kernel can also be reduced with a proper constraint on it. The former produces more visually pleasant result while the latter usually leads to more robust kernel estimations.

Shan et al. apply the recent findings derived from image statistics that in spatial domain, the natural image gradient should follow a heavy-tailed distribution [9] and make such constraint on their latent image in gradient domain [10]. Goldstein et al. use the power law of natural image in frequency domain

\[ |\hat{I}(\omega)| \propto ||\omega||^{-\beta}, \]

where \( \hat{I} \) is the Fourier transform of a natural image, \( \omega \) is the frequency variable and \( \beta \) is assumed to be roughly two [11]. Yue et al. further exploit the power spectrum of the natural images and propose a new model for the blur kernel in frequency domain [12]. However, the image statistics of both spatial and spectrum domain may not hold for muscle images since they are significantly different from the natural images and often contain more special shape and texture pattern.Weak edges, subtle curves or corners included in muscle images usually convey important pathological meanings and diagnostic clues. The sparsity on the gradient map for the latent image is more subtle curves or corners included in muscle images usually contain more special shape and texture pattern. Weak edges, subtle curves or corners included in muscle images usually convey important pathological meanings and diagnostic clues. The sparsity on the gradient map for the latent image is a more general and robust regularization promising for muscle images. In this context, Whyte et al. adopt \( l_1 \) sparsity to constrain the gradient [13] of the latent image. Krishnan et al. further improve this term by normalizing the \( l_1 \) norm with the \( l_2 \) norm to better express the nature of the blur [14]. Xu et. al adopt non-linear penalties to \( l_1 \) norm [15] and sophisticated \( l_0 \) norm [16] [17] of the gradient of the latent image. The \( l_1 \) norm [14] or the \( l_2 \) norm [19] are typically used to regularize the estimated kernel.

Without proper constraints, ring artifacts are usually produced due to outliers/noise of the data or the saturated pixels. Shan et al. propose a heuristic method for ring effect reduction by localizing the smooth regions of the latent image and suppress their gradients [10]. Whyte et al. examine the reasons why ring artifacts emerge and propose that it is because of the nonlinear mapping caused by saturated pixels and the lack of constraints when solving on the near-zero domain of the transform made by the kernel [13]. They propose to use a mask to filter out those saturated pixels to avoid wrong estimations and also use some regularizations to further forbid those errors from propagating to good estimations. Cho et al. propose a method in a non-blind deconvolution with similar rationale but the mask and the outliers are explicitly modeled and optimized, leading to a better result [20].

The context of aforementioned deblur algorithms is spatially uniform which assumes a constant kernel across the entire image. Despite their amazingly good performance [21], this is not true in either natural images taken with a camera or the microscopic muscle images in this paper. Several works [22] [23] [17] extend their kernel models to 3D or 6D degree of freedom (DoM) describing a complete motion domain caused by in-plane translations, rotations, and out-of-plane rotations. However, the performance of the deblur does improve significantly [21]. We show in this paper that uniform assumption is good for local regions of the muscle image while non-uniformity must be considered in the global domain.

### III. Muscle Image Enhancement

In this section, we introduce the proposed spatially non-uniform deblur framework involving blur kernel estimation and muscle image deconvolution. We do not assume the blur kernel for muscle images is known and explicitly estimate it. The proposed kernel estimation algorithm is overall spatially variant but can be separated into a group of spatially invariant estimations. These estimations are made on a few random subregions of the muscle image. Estimated kernels are treated as seeds and are propagated to their neighboring regions as the initializations for kernel estimation. We show in the experimental results that the proposed scheme has fast convergence maintains good coherence of the image structure. An overall flowchart of the proposed method is shown in Fig. 2.

#### A. Kernel Estimation

In the spatially invariant blur kernel estimation context, one effective Bayesian inference approach, namely, the MAP model, is frequently used. Suppose the latent image (or a subregion) \( X \) is blurred with a kernel \( k \) with some additive noise \( \epsilon \) that follows a specific statistical distribution. The degradation of blur and defocus on a latent image can be both modeled as convolution computation written as:

\[
I = X \otimes k + \epsilon, \quad (1)
\]

where \( I \) denotes the degraded image, \( X \) is the latent distortion-free image, and \( \otimes \) denotes convolution operation. Note that there is an option to reorganize \( k \) or \( X \) to write the convolution as one matrix multiplies the other as in Eq. \[2\]

\[
I = AX + \epsilon, \quad (2)
\]

where \( A \) is the Toeplitz form of the kernel \[2\]. However, this is not necessary for our algorithm and all terms are written as their original version. The blur kernel \( k \), or PSF, can be either a motion trajectory to model the physical motion blur, or a Gaussian distribution to model defocus, or both (in which the kernel usually shows a blurred version of a motion trajectory). In MAP-estimation framework, deblur algorithms typically assume the pixels of the image are independent and attempt to maximize the posteriori \( p(X, k|I) \):

\[
\max_{X, k} p(X, k|I) \propto \prod_{i=1}^{N} p(I|x_i, k)P(k)p(X), \quad (3)
\]

1Suppose the 2D image locates on the plane determined by the \( x \) and \( z \) axes, the 3D modeling is either rotations along the three axes \( \{\theta_x, \theta_y, \theta_z\} \), or the translations on \( x \) and \( z \) axes and the rotation on visual axis \( z \) \( \{\tau_x, \tau_y, \tau_z\} \). The 6D modeling is to use both. See [21] for more details.

2Each row of \( A \) corresponds to a vectorized version of \( k \) with a phase shifted by one element (and reversed for convolution).
where $p(I|x_i,k)$ is the likelihood of the degraded image and $X = \{x_i| i = 1...N\}$ where $N$ denotes the number of pixels of the latent image. $p(k)$, $p(x)$ are the prior probability of the kernel and the latent image, respectively. This form can be interpreted as an energy minimization problem by defining $E(X,k) = -\log * (p(X,k|k))$ and write Eq. 1 as:

$$\min_{X,k} E(X,k) \propto \sum_{i=1}^{N} E(I|x_i,k) + E(k) + E(X),$$

where $\sum_{i=1}^{N} E(I|x_i,k)$ is referred to as the data fidelity term. $E(k)$ and $E(X)$ are the priors of the blur kernel and the latent image, respectively. In the following sections, we introduce the choices of the MAP terms in the proposed muscle image enhancement framework and provide the optimization solution.

1) Data Fidelity and Noise Model: The purpose of the data fidelity term is to constraint the estimated latent image not to deviate too much from its blurred version. Recent findings show that gradient plays an essential role during the kernel estimation [10]. In fact, $X$ is not necessarily a “real” image but can be either gradient map $\{\partial_x, \partial_y|X\}$ or some “unnatural” representations of the image [19] [17]. Due to the severe ill-posed nature of this problem, these options usually provide more helpful information of the blur kernel than the natural image estimated during the optimization or the initial blurred image. After the MAP optimization reaches the convergence, only the estimated kernel is used and the final output image is computed using some non-blind deconvolution approaches with image priors to suppress artifacts. In this paper, we propose to use gradient map as the input to the kernel estimation problem due to its simplicity and efficiency. The blurry muscle image is converted to gray scale and two derivative kernels are used to obtain the gradient maps at both the vertical and horizontal directions:

$$\nabla X = \{\partial_x X, \partial_y X\} = \{X \otimes \partial_x, X \otimes \partial_y\},$$

where $\otimes$ denotes the convolution operation and

$$\partial_x = \begin{bmatrix} -1 & 1 \\ 0 & 0 \end{bmatrix}, \partial_y = \begin{bmatrix} -1 & 0 \\ 1 & 0 \end{bmatrix}.$$
algorithm (ISTA or FISTA) [27] can be used to find its solution efficiently, providing we adopt Bayesian inference and assume the noise follows the white Gaussian noise model in Eq. [5]. Other priors, such as the prior in [10] and the sophisticated l0 norm [17], are not used because they is computational efficient despite their promising performance. The total variation of the gradient tends to over-smooth the latent image. The normalized l1 norm in [14] is highly non-convex and has many local minima, which hinders the successful estimation. works well but it is usually slow to optimize.

3) Kernel Prior: Unlike typical motion blur problems in which the blur kernel can be modeled as a motion trajectory in 3D space, the degradation of the microscopic muscle image is largely the defocus problem with high variances in 2D space of the entire slide. Although we explicitly confine the blur kernel to be Gaussian at the initialization stage of the optimization, the weight assigned to this constrain is quickly decreased and to be Gaussian at the initialization stage of the optimization. The degradation of the microscopic muscle image is largely the defocus problem with high variances in 2D space of the entire slide. Although we explicitly confine the blur kernel to be Gaussian at the initialization stage of the optimization, the weight assigned to this constrain is quickly decreased and diminished. We adopt l2 norm to suppress the noise. l1 norm tends to over-suppress the kernel in our case though it is a good regularization in common natural image deblurring problem. The kernel prior used in our method is written as:

$$E(k) = \eta p(k|\sigma) + \nu ||k||_F^2,$$

$$p(k|\sigma) = \left| |k| a,b \right| - \frac{1}{2\pi\sigma^2} \exp\left(-\frac{a^2 + b^2}{2\sigma^2}\right)||_2^2,\quad (7)$$

where \(p(k|\sigma)\) denotes the likelihood of the kernel to be a circular Gaussian with the parameter \(\sigma\) which takes \((a,b)\) as variables. \(\eta\) and \(\nu\) are weights of controlling the importance of both terms. \(\eta\) is decayed exponentially and is set to 0 after a few iterations.

4) Optimization: Combining Eq. [8] and Eq. [7] to Eq. [1] the overall optimization of the proposed deblur is written as:

$$\min_{\nabla X, k} \|\nabla X \otimes k - \nabla I\|_F^2 + \lambda \|\nabla X\|_F^2 + \eta p(k|\sigma) + \nu ||k||_F^2,\quad (8)$$

where \(\lambda, \eta\) and \(\nu\) are weight terms.

We discuss the detailed configurations of these parameters in the experiment section and the user does not have to. Eq. [1] is solved using Alternating Minimization (AM) and obtain the estimated blur kernel and the gradient of the latent image (which is an “unnatural” representation of the latent image and is not used after the kernel is estimated):

$$\min_{\nabla X} \|\nabla X \otimes k - \nabla I\|_F^2 + \lambda \|\nabla X\|_F^2,\quad (9)$$

and

$$\min_k \|\nabla X \otimes k - \nabla I\|_F^2 + \eta p(k|\sigma) + \nu ||k||_F^2.\quad (10)$$

To optimize Eq. [9] we use ISTA algorithm by replacing matrix multiplications with convolutions as shown in algorithm [1] and find the solution of the latent muscle image in gradient domain. Note that \(\Phi_\pi(\cdot)\) denotes a rotation of 180° operation on a matrix \(\pi\). This rotation operation replaces the original matrix transpose when 1) typical ISTA algorithm or 2) the Toeplitz form for convolution as in Eq. [2] is used. \(\text{sign}(\cdot)\) is the element-wise sign function for a matrix and \(\circ\) denotes the matrix element-wise multiplication. Note that we obtain the updates for \(\partial_x X\) and \(\partial X_y\) individually using Eq. [9] in Eq. [10].

Algorithm 1 Gradient map update

1: Task: Obtain the solution of the latent image in gradient domain \(\nabla \tilde{X}\) under \(l_1\) norm regularization;
2: Initialization: Observed gradient image \(\nabla I\) in current resolution level, initial latent image \(\nabla X_0 = \nabla I,\) initial kernel \(k^0\) at coarsest resolution level or the optimization result \(k = \tilde{k}\) from a coarser resolution level, regularization parameter \(\lambda\), ISTA threshold \(\zeta\), maximum inner iteration number \(T\), current iteration \(t = 1;\)
3: repeat
4: Set \(\nabla Y \gets \nabla X^t - \zeta \Phi_\pi(k) \otimes (k \odot \nabla X^t - \nabla I).\)
5: Set \(\nabla X^{t+1} \leftarrow \text{sign}(\nabla Y) \odot \max(|\nabla X^t| - \lambda \zeta, 0).\)
6: Compute the energy cost in Eq. [9].
7: Set \(t \leftarrow t + 1.\)
8: until \(t > T\) or energy cost convergence reached.
9: Set \(\nabla \tilde{X} \leftarrow \nabla X^t.\)

Algorithm 2 Kernel update

1: Task: Obtain the solution of the blur kernel \(\tilde{k}\) under both \(l_2\) norm and Gaussian similarity regularization;
2: Initialization: Observed gradient image \(\nabla I\) at current resolution level, regularization parameter \(\eta\) and \(\nu\) decayed by \(\Delta \eta\) at each iteration;
3: Compute the least square estimation of the kernel \(\tilde{k}\) in Eq. [12].
4: if \(\eta \neq 0\) then
5: Compute the maximum likelihood solution of the approximate Gaussian function \(\mathcal{N}(0, \hat{\sigma}) \simeq \hat{k}\) in Eq. [13].
6: else
7: Set \(\tilde{k} \leftarrow \tilde{k}.\)
8: end if
9: Normalize the estimated kernel \(\hat{k} \leftarrow \hat{k}/||\hat{k}||_F.\)

We present the details of solving the optimization problem for kernel \(k\) in Eq. [10]. We first solve \(k\) with \(l_2\) regulation in a least square minimization:

$$\hat{k} = \arg\min_k E_k,$$

$$= \arg\min_k \|\nabla X \otimes k - \nabla I\|_F^2 + \nu ||k||_F^2,\quad (11)$$

whose solution, according to the Parseval’s theorem [19], is efficiently obtained in closed-form by Fast Fourier Transform (FFT) and setting derivative \(\frac{\partial E_k}{\partial F(k)} = 0\) [19]:

\(^3\)This can be implemented via the “rot90(0, 2)” command in MATLAB.
\[ \hat{k} = F^{-1} \left( \frac{F(\nabla X) \otimes F(\nabla I)}{F(\nabla X) \otimes F(\nabla X) + \nu 1} \right) \]
\[ = F^{-1} \left( \frac{F(\partial_x X) \otimes F(\partial_x I) + F(\partial_y X) \otimes F(\partial_y I)}{F(\partial_x X) \otimes F(\partial_x X) + F(\partial_y X) \otimes F(\partial_y X) + \nu 1} \right), \quad (12) \]

where \( F \) and \( F^{-1} \) is the Fourier/inverse Fourier transform pair \(^5\) and \( 1 \) denotes a matrix whose elements are uniformly 1. Then, we find a Gaussian blur kernel \( \mathcal{N}(0, \hat{\sigma}) \) closest to \( \hat{k} \) with maximum likelihood inference:

\[ \hat{k} \sim \mathcal{N}(0, \hat{\sigma}), \]
\[ \hat{\sigma} = \arg\max_{\sigma \in \Theta} \ell(\sigma; \hat{k}, \mathcal{N}(0, \hat{\sigma})), \quad (13) \]

where \( \hat{\sigma} \) is the maximum likelihood solution of the parameter and \( \Theta \) is its value domain. Finally, we search in a small window for this parameter:

\[ \hat{\sigma} \pm \Delta \sigma, \quad (14) \]

To find a local minima for the cost function in Eq. (10) We use brute force here and search for the result for each possible value of \( \hat{\sigma} \pm \Delta \sigma \), where \( \sigma_i \) is some preset step sizes. Eq. (13) and Eq. (14) are served as regularizations to control the overall shape of the estimated kernel and to suppress noise. We empirically find out that they are helpful only in the first few iterations. Thus, we gradually decrease the value of the weight \( \nu \) to zero after a few iterations. The brute force search in Eq. (14) looks ad-hoc but it is fast in practice. In fact, we are not the first to propose this approach. Hu et al. assume their estimated kernel to be plate-shaped and use brute force to search for its axis parameters \(^6\). They claim that the computational cost is not a problem. In addition, we normalize the estimated kernel to keep its \( l_1 \) norm to be 1 in order to preserve its energy at each iteration of the optimization. The kernel update steps are summarized in Algorithm 2. We follow the popular coarse-to-fine strategy using pyramid representation of the muscle image as Fig. 3 depicts. We conduct our blur kernel estimation algorithm from low to high resolution levels. Each resolution level provides an estimation of the kernel (with an increasing size) to the next finer level. At each resolution level, we run Algorithm 1 and Algorithm 2 several but not too many iterations for refinement. The overall kernel estimation algorithm is summarized in Algorithm 3.

**B. Latent Image Recovery**

After the kernel for the finest resolution level is estimated, we deconvolve the muscle image with it and obtain the estimation of the latent image. Note that we only obtain the latent image in gradient domain in previous steps. Numerous works for non-blind (with knowledge of the kernel) deconvolution have been proposed in literature, ranging from the traditional

\(^5\) The Fourier/inverse Fourier transform pair is implemented with fast (inverse) Fourier transform (**FFT** and **IFFT**). In MATLAB, we use "fft2" to compute the coefficients in frequency domain for gradient maps and use "otf2psf" to compute the inverse Fourier transform to convert the estimated blur kernel to spatial domain. This is because "fft2" centers the input image at (1, 1) while "otf2psf" centers at the geometric center.

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Algorithm 3 Overall blur kernel estimation

Task: Obtain the solution of the blur kernel $\hat{k}$;

Initialization: Observed image $I$, set the initial blur kernel $k_w^0 \leftarrow \delta$ (Dirac function) or as an estimated kernel from the neighboring region $k_w^0 \leftarrow k'$, regularization parameter $\lambda$, $\eta$ and $\nu$, total outer iteration number $N$ and the current iteration $n$, total pyramid levels $\Omega$ and the current processing resolution level $\omega_{ini} \leftarrow (k_w^0 = \delta) \Omega : \Omega$, where $\omega = 1$ relates to the coarsest resolution level of the image;

Compute the image pyramid $\{I_\omega\}$ with $\Omega$ levels for $I$.

for $\omega = \omega_{ini}$ to $\Omega$ do

Initialize the gradient map at the current resolution level: $\nabla X_w^0 \leftarrow (\omega = 1) \nabla I_\omega : \nabla X_{\omega-1}$. Set $\nu$ as its initial value.

for $n \leftarrow 1$ to $N$ do

Update the blur kernel $\hat{k}_w^n$ for $\nabla I_\omega$ at the current resolution level with Algorithm 2 by inputting $\nabla X = \nabla X_w^n$.

Update the gradient map $\nabla X_w^{n+1}$ of the latent image at the current resolution level with Algorithm 1 by inputting $k = \hat{k}_w^n$.

end for

if $\omega \neq \Omega$ then

Upscale $\hat{k}_\omega$ and $\nabla \hat{X}_\omega$ to the next finer resolution level.

end if

end for

The estimated kernels are treated as seeds and non-seeds in Algorithm 1 to estimate the kernels of the other sub-images, the rationale behind this method is that the estimated blur kernels are propagated to their neighboring sub-regions to accelerate their kernel estimations.

IV. EXPERIMENTAL RESULTS

A. Experiment Settings

We obtain 44 microscopic muscle images using an Olympus VS 120 advanced optical microscope, each of which has a large size. Thus, the muscle images used in our experiments are cropped with large size, assuming each channel of the muscle image data is normalized to range in $[0,1]$. We empirically set $\lambda = 80$, $\eta = 15$, $\nu = 6$ and decay term $\Delta \nu = 2$ and do not make any further tunings. We assume the kernel size to be 15 pixel$^2$ and the size of the image pyramid $\Omega$ is set as 5. We test the proposed framework on a desktop computer with Intel Xeon E5-1650 3.50 GHz (12 threads) CPU and 128GB memory.

B. Synthesis Blur

In this experiment, we manually crop 20 muscle sub-images (round 2000 by 1000$^2$) that we consider as sharp ones without visually obvious blur or defocus. We synthesize a number of Gaussian blur on them to simulate the spatially variant blur and defocus. We denote $b_i = \{(a_i, b_i), \sigma, \sigma_i\}$ as a blur of the latent muscle image centered at the coordinate $(a_i, b_i)$ and the size of the synthesis Gaussian blur kernel is $\sigma = \{(0.1/255, 0.2/255, ..., 0.5/255\}$.

The number of resolution levels of the image pyramid $\Omega$ is set as 5. We further speedup the algorithm, we randomly randomly pick up $n$ sub-image centers away from the boundary (to avoid picking sub-images that have too few number of neighbors). We run Algorithm 3 and estimate their blur kernels individually. The estimated kernels are treated as seeds and are propagated to their neighboring sub-images as initializations during their kernel estimation. The rationale behind this method is that most neighboring sub-image share similar blur degree and thus should have similar blur kernels (Globally, they still display high non-uniformity). The sub-images having their kernels propagated by seeds are not represented with pyramid structure during the kernel estimation. Thus, the computation is accelerated by skipping the kernel estimation.

Fig. 5. Local kernel propagation. The estimated blur kernels $\hat{k}$ and $\hat{k}'$ are propagated to their neighboring subregions to accelerate their kernel estimations.
where $\rho(m, n)$ is the standard deviation of the blur kernel. It is determined by the distance between $(m, n)$ and the blur center $(a, b)$:

$$\rho(m, n) = \sigma_s \cdot \exp\left\{ -\frac{|(a, b) - (m, n)|^2}{2\sigma_l} \right\},$$

where $\sigma_s$ is the blur strength of the kernel $b_i$ and is decayed as the location deviates from the blur center and is controlled by the parameter $\sigma_l$. We randomly set the center of the blur kernel and set $\sigma_s \in (0.5/255, 4.5/255]$, $\sigma_l = 100$. Figure 6 shows a distortion free muscle image corrupted by the defined synthesis blur with $\sigma_s = 5/255$. We uniformly split the clean images into four distortion levels degraded by different number of synthesis Gaussian kernels and different $\sigma_s$. The settings of the distortion levels are described in Table I. At each level, we randomly choose the value of $\sigma_s$ uniformly distributed at the interval described in [1] whose value is for pixel value range $[0, 255]$ and is divided by 255 in our experiment.

We test the proposed deblur algorithm of our framework and set parameters as mentioned before without further tweaking. We compare our the visual quality of our results with the state-of-art spatially non-uniform deblur algorithm by L. Xu et al. [17] using peak signal to noise ratio (PSNR) as the image quality metric. The

C. Real Blur

We test our algorithm on 12 cropped muscle images (around 2000 by 1000) with significant noticeable blur. To quantitatively evaluate the performance, we use a popular blind image
TABLE I
SETTINGS OF DIFFERENT LEVELS OF SYNTHESIS DISTORTION.

| distortion level | number of Gaussian blurs | $\sigma_s$ |
|------------------|--------------------------|------------|
| Level I          | 5                        | $\in (0.5,1.5]$ |
| Level II         | 10                       | $\in (1.5,2.5]$ |
| Level III        | 15                       | $\in (2.5,3.5]$ |
| Level IV         | 20                       | $\in (3.5,4.5]$ |

TABLE II
COMPARISON OF THE ENHANCEMENT RESULTS FOR SYNTHESIS BLUR. AVERAGE PSNR VALUE IS COMPARED AT EACH DISTORTION LEVEL.

|          | Level I | Level II | Level III | Level IV |
|----------|---------|----------|-----------|----------|
| L. Xu [17] | 42.34   | 36.56    | 30.10     | 23.65    |
| proposed  | 47.64   | 41.26    | 32.13     | 25.02    |

TABLE III
COMPARISON OF THE ENHANCEMENT RESULTS FOR REAL BLUR USING BLIND IQA SCORE.

| Image # | IQA score | IQA score (proposed) | IQA score ( [17] ) |
|---------|-----------|----------------------|--------------------|
| 01      | 0.28      | 0.44                 | 0.37               |
| 02      | 0.43      | 0.49                 | 0.43               |
| 03      | 0.54      | 0.57                 | 0.56               |
| 04      | 0.14      | 0.39                 | 0.20               |
| 05      | 0.58      | 0.53                 | 0.56               |
| 06      | 0.38      | 0.40                 | 0.42               |
| 07      | 0.66      | 0.69                 | 0.67               |
| 08      | 0.40      | 0.77                 | 0.47               |
| 09      | 0.34      | 0.66                 | 0.39               |
| 10      | 0.43      | 0.64                 | 0.46               |
| 11      | 0.44      | 0.43                 | 0.48               |
| 12      | 0.47      | 0.65                 | 0.46               |

quality assessment (blind IQA) [30] to compare the results with [17]. The blind IQA in [30] is a image quality evaluation scoring system which returns a score regarding to the image’s sharpness, noise, transmission loss, etc. without the necessity of the availability of the distortion-free version of the image. We normalize the score to the range [0,1] for convenience. Table III summarizes the blind IQA scores for the original blur images, enhanced by the proposed algorithm, and those by [17]. It is observed that the proposed algorithm outperforms the [17] on 9 out of 12 blur muscle images, although [17] exhibits a little more robustness on certain images. The parameters for both compared methods are set with consistent configurations we empirically choose and defaulted by the authors, respectively.

The proposed algorithm is also computationally efficient due to its simple design. The average computation time for one cropped muscle image of its CPU implementation on Matlab, compared with [17], is presented in figure 8. The proposed algorithm is significantly efficient compared with the algorithm in [17], since the latter is designed for natural image deblur which is typically not so large as muscle images are.

V. CONCLUSION

We present a novel image enhance system in which a simple but effective deblur algorithm specialized for muscle image is involved. The system is designed with one-click-style interface which frees the users from laborious parameter tunings. The effectiveness of the algorithm is verified on both synthesis and practical blur quantified by an objective image quality evaluation metric.

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Fig. 7. Examples of enhanced muscle images by the proposed algorithm. The figures in the left column are the original blur image and the enhanced images are in the right column. Best reviewed in enlarged resolution.

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