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Combining weighted curvelet accumulation with motion vector duty cycle for nonuniform video deblurring

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ABSTRACT

Since object motion and camera shake can cause motion blur, there are some blurry frames in the captured videos by hand-held camera. In order to solve the above problem, we propose a nonuniform video deblurring method that combines weighted curvelet accumulation with motion vector duty cycle. In the proposed method, firstly we propose a weighted curvelet accumulation method that can synthesize the multiple adjacent frames in the frequency domain for estimating the initial latent sharp frame. Secondly, because the duty cycle has a close relation with the accuracy of the blur kernel, we propose a motion vector duty cycle estimation method by utilizing the inter-frame correlation information and the estimated initial latent sharp frame to improve the blur kernel accuracy. Finally, we build a novel nonblind video deblurring model by fully utilizing the spatiotemporal information and the estimated blur kernel for obtaining the deblurred frame. Experimental results on the numerous videos show that the proposed method achieves the state-of-the-art results either in subjective vision or in objective evaluation.

1. Introduction

The captured videos by hand-held camera often contain disappointing blurry frames caused by camera shake and object motion. How to remove the blur is a worth studying problem. Under reasonable hypotheses, the blur frame can be modeled mathematically as a convolution,

$$B = K * L + N, \tag{1}$$

where B, L, and N denote the blurry frame, the sharp frame, and additive noise respectively. K is the unknown blur kernel and * is convolution operator. Numerous traditional methods attempt to remove the motion blur by explicitly solving an inverse and inherently ill-posed deconvolution problem.

Some other methods obtained the deblurred frame without deconvolution [1–4]. Tan et al. compared a blurry patch directly against the sharp candidates in spatial domain, in which the nearest neighbor matches could be recovered [1]. However, the blurry regions and the sharp regions in a frame are difficult to divide accurately in airspace. Delbracio and Sapiro proposed a removing camera shake method for the burst images via weighted Fourier burst accumulation [2,3]. Fourier transform also was used in video deblurring domain, such as combining information from the block of the nearby frames in the Fourier domain [4]. However, Fourier transform only can deal with the uniform blurry frame, hence a frame was splitted into blocks for deblurring the nonuniform blurry frame. It also has the problem that which size of the blocks is suitable. On the one hand, in the large size block, the larger it is, the lower sharpness of the deblurred frame is. On the other hand, in the small size block, it likely bring error into the deblurred frame and spent longer running time.

In order to overcome the above defects, we propose a weighted curvelet accumulation method which can synthesize the multiple adjacent frames without block for obtaining the initial latent sharp frame. Because the curvelet coefficient includes the phase information, it can deal with the nonuniform blurry frame without block. Curvelet transform is widely used in image denoising [5], feature extraction [6], compressive sensing deconvolution [7], face recognition [8], and remote sensing image fusion [9]. However, curvelet transform never appears in video deblurring domain at present. Unlike wavelet transform and other related systems, curvelet transform which takes the form of basic elements exhibits a very high directional sensitivity and anisotropy. Therefore, curvelet transform is more suitable to analyze image edge than wavelet transform. Curvelet transform is multiscale transform that represents an image in terms of not only shifted versions of a low-pass scaling function but also dilated and rotated versions of a prototype band-pass curvelet basis function. It is different to wavelet basis function, the band-pass curvelet basis function has an elongated envelope with the envelope's length scaling as its width squared. Curvelet transform is much more effective than traditional transform to represent edge and other singularity along curve. Therefore, the estimated initial latent

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sharp frame by the proposed weighted curvelet accumulation method is sharper than that by the representative methods.

The accuracy of duty cycle is related to the blur kernel. Traditional methods assumed the duty cycle is a known value or a fixed value in every frame. Kim et al. proposed a single energy model that simultaneously estimated the optical flow and the latent frame [10]. Cho et al. presented a framework that transfers the sharp details to the blurry frames by patch synthesis [11]. These methods both used initial flow and approximate kernel to estimate the duty cycle that was assumed to be a fixed value in every frame. In fact, in order to adapt the shooting scene in the different lighting, the duty cycles in the adjacent frames are variable when the camera automatically exposes. Moreover, when objects do naturally motion which includes nonlinear and nonplanar motion, the duty cycle of every pixel in a frame is different. In order to improve the blur kernel accuracy, we propose a duty cycle estimated method by fully utilizing the inter-frame correlation information, and we call it as motion vector duty cycle estimation method.

The contributions of this paper are summarized as follows.

(1) We propose a weighted curvelet accumulation method which can synthesize the multiple adjacent frames in the frequency domain for estimating the initial latent sharp frame.

(2) We propose a motion vector duty cycle estimation method to improve the blur kernel accuracy.

(3) We build a novel nonblind video deblurring model by fully utilizing the spatiotemporal information for obtaining the deblurred frames.

The remainder of this paper is organized as follows. Section 2 discusses the related work. Section 3 describes the proposed weighted curvelet accumulation method, the proposed motion vector duty cycle estimation method, and the proposed nonblind video deblurring model respectively. The experimental results and discussions are illustrated in Section 4. Section 5 is the conclusions.

2. Related work

In the early stage of video deblurring, researchers are focus on extracting the blurry region, such as foreground extraction and deblurring [12], circular blurring paths are computed in polar coordinate [13], optical flow of motion object in static background [14], motion object detection by a background extraction method [15], layer motion and segmentation by optical flow [16], and downsample-interpolation technique and edge-preserving regularization [17]. These methods only can be used to deblur the extracted blur regions under specified condition. However, when the frame is entire blurry, these methods are inapplicability.

As the development of research, the latest video deblurring methods are more concentrated on deblurring the entire blurry frame, such as a sampling-based framework that allows for robust scene-space video processing [18], removing motion blur with space–time processing [19], and a feature-based frame rate up-conversion algorithm [20].

The mainstream video deblurring method is based on the blur kernel estimation and deconvolution. Kim et al. first proposed a segmentation-free dynamic scene deblurring method [21] and further improved this method by utilizing the advantage of the spatial and temporal regularization [10]. Dong et al. extracted salient edges from an intermediate latent image solved by combining the predicted edges and the low rank prior when estimating blur kernels [22]. Kumar estimated the point spread function (PSF) parameters based on the concepts of histogram of oriented gradients and statistical properties [23]. Li et al. proposed an automatic calculation method to estimate duty cycle for extracting the accurate global motion blur kernel [24]. A non-local kernel regression model exploited both the non-local self-similarity and the local structural regularity properties in natural images [25]. However, in these methods, the duty cycle was assumed to be a known value or a fixed value in every frame. In fact, the duty cycle of every pixel in a frame of real video is different.

Blurry frame could also be indicated by the inter-frame multiple images accumulation. Tai et al. firstly proposed a projective motion blur model with a sequence of transformation matrices [26]. Shen et al. proposed a kernel mapping regularized method which estimated the blur kernels by integral distribution during exposure [27]. Blurry image was formulated as an integration of some clear intermediate images after optical based transform [28]. Cho et al. proposed an approximate blur model to estimate blur function of video frame [11]. Zhang and Yao proposed a removing video blur approach that could handle nonuniform blur with non-rigid inter-frame motions [29]. Based on these inter-frame multiple images accumulation methods, a motion vector duty cycle estimation method is proposed for estimating accurate blur kernel.

Another common video deblurring method is residual deconvolution. Yuan et al. first proposed residual deconvolution to deblur image using the blurred noisy image pairs [30]. Then, residual deconvolution was widely introduced to video deblurring domain, such as residual deconvolution with an adjacent unblurred frame [31], residual deconvolution based on a blurred–unblurred frame pair [32], bidirectional motion compensation [33], and a bundle of kernels [34]. However, in the residual deconvolution process, the latent sharp frame was updated by fixed blur kernel. Therefore, the estimated blur kernel needs high accuracy. Moreover, residual deconvolution also needs to estimate an initial latent sharp frame.

Some video deblurring methods estimated sharp frame by synthesis. Gong et al. proposed a preprocessing strategy that employed anisotropic diffusion and shock filter [35]. Rabbani proposed an initial clean data estimation method in discrete complex wavelet transform [36]. However, the above methods only utilized a frame to estimate sharp frame. Qiao et al. presented a PatchMatch-based search strategy to search for a sharp superpixel to replace a blurry region [37]. But the each sharp superpixel was selected from a frame, when a region in all the adjacent frames are not enough sharp, the method cannot restore the blur region. Some other methods that utilized the multiple adjacent frames for estimating the sharp frame would obtain more prior information. Su et al. introduced a deep learning solution to video deblurring domain where a Convolutional Neural Network was trained end-to-end to learn how to accumulate information across frames [38]. Tan et al. merged a sharp frame from the different regions of the adjacent frames, but the blurry regions and the sharp regions were difficult to divide accurately in the airspace [1]. Delbracio and Sapiro proposed a sharp frame synthetic method in Fourier domain [4]. However, Fourier transform only was used to remove uniform blur.

In order to take the advantage of the curvelet transform which includes phase information, we propose a weighted curvelet accumulation method for obtaining the initial latent sharp frame. Based on the inter-frame multiple images accumulation, we propose a motion vector duty cycle estimation method to improve the blur kernel accuracy. Finally, the deblurred frame is obtained by minimizing the proposed nonblind video deblurring model that is built by fully utilizing the spatiotemporal information and the estimated blur kernel.

3. Proposed method

3.1. Weighted curvelet accumulation

The rationale of the proposed weighted curvelet accumulation method is that each frame of a video is generally different blur due to camera shark has a random nature. An object is blurry in the some frames and sharp in the other frames. In order to utilize the sharp regions of the adjacent frames to restore the blurry regions of a blurry frame, we propose a weighted curvelet accumulation method that can obtain an initial latent sharp frame by synthesizing the details from the adjacent frames. The detailed steps of the proposed weighted curvelet accumulation method are as follows.

The first step is to register the adjacent frames to the blurry frame by utilizing a nonuniform registration method which builds a warping-based motion model based on a bundle of spatially variant homography