

Enhancing Video Deblurring using Efficient Fourier Aggregation

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Abstract— Video Deblurring is a process of removing blur from all the video frames and achieving the required level of smoothness. Numerous recent approaches attempt to remove image blur due to camera shake,either with one or multiple input images, by explicitly solving an inverse and inherently ill-posed deconvolution problem.An efficient video deblurring system to handle the blurs due to shaky camera and complex motion blurs due to moving objects has been proposed.The proposed algorithm is strikingly simple: it performs a weighted average in the Fourier domain, with weights depending on the Fourier spectrum magnitude. The method can be seen as a generalization of the align and average procedure, with a weighted average, motivated by hand-shake physiology and theoretically supported, taking place in the Fourier domain. The method’s rationale is that camera shake has a random nature, and therefore, each image in the burst is generally blurred differently.The proposed system has effectively deblurred the video and results showed that the reconstructed video is sharper and less noisy than the original ones.The proposed Fourier Burst Accumulation algorithm produced similar or better results than the state-of-the-art multi-image deconvolution while being significantly faster and with lower memory footprint.The method is robust to moving objects as it acquired the consistent registration scheme.

Keywords— *deblurring, motion blurs,camera shake*

I. INTRODUCTION

Video capture has become very popular in recent years, largely because of the widespread availability of digital cameras. However, motion blur is unavoidable in casual video capture due to camera shake and object motion during exposure.Motion blur is the result of the relative motion between the camera and the scene during image exposure time.This includes both camera and scene objects motion.As blurring can significantly degrade the visual quality of images, photographers and camera manufactures are frequently searching for methods to limit the phenomenon.Camera shakes happen more often with a video camera. Significant camera shake will cause video frames to be blurry.Restoring shaky videos not only requires smoothing the camera motion and stabilizing the content, but also demands removing blur from video frames.However, video blur is hard to remove using existing single or multiple image deblurring techniques.Thus, video deblurring is an important but challenging task in video processing.

Deblurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. In video, the number of frames are flashed on a screen for a short time one after another and then immediately replaced by the next one. In film frame or video frame is one of the many still (or nearly so) images which compose the complete moving pictures. These moving pictures are known as video. A complete video contains number of video frames. Two frames separated by a line that is known as frame line.Camera motion is one of the prime causes for poor image quality. Video captured by cameras contain significant camera shake or fast moving object, causing many frames of video to be blurry.

Handheld video capture devices are now commonplace. As a result, video stabilization has become an

essential step in video capture. While stabilization techniques have improved dramatically, the remaining motion blur is a major problem with all stabilization techniques. This is because the blur becomes obvious when there is no motion to accompany it, yielding highly visible “jumping” artifacts. In the end, the remaining camera shake motion blur limits the amount of stabilization that can be applied before these artifacts become too apparent. The most successful video deblurring approaches use information from neighboring frames to sharpen blurry frames, taking advantage of the fact that most handshake motion blur is both short and temporally uncorrelated. By borrowing “sharp” pixels from nearby frames, it is possible to reconstruct a high quality output.

Motion blur caused by camera shake has been one of the prime causes of poor image quality in digital imaging, especially when using telephoto lens or using long shuttle speed. Camera shaking, which causes blurry frames in a video sequence, is a chronic problem for photographers. Camera and object motion blur effects become more apparent when the exposure time of the camera increases due to low-light conditions. The main difference between video deblurring and image deblurring is the addition of a time component. The presence of this component adds a new layer of information, such as motion, which is inexistent in image deblurring. Motion in a video sequence is a new source of blur that can be handled using several methods. Image or video deblurring has been extensively studied and many proposed methods have yielded great success.

II. LITERATURE SURVEY

There is a rich literature in video deblurring and Feature detection and extraction.Here we discuss the most related work.

Congbin Qiao et al. [1] present a non-uniform motion model to deblur video frames. Non-uniform motion blur due to object movement or camera jitter is a common phenomenon in videos. The author proposed a method based on superpixel matching in the video sequence to reconstruct sharp frames from blurry ones. However, this system fails if no sharp superpixels can be found from other frames of the video.

Sunghyun Cho et al. [2] propose a method for removing non-uniform motion blur from multiple blurry images. One is that it shows some artifacts around the boundaries of different motions in restored images. Blurry regions on boundaries of the foreground object still remain. This artifact is inevitable due to missing information of hidden pixels behind the foreground objects. Second, like existing segmentation algorithms, segmentation is not performed well on textureless regions because it is difficult to determine the motion in such regions. Therefore, this method is less effective if the input images are not textured.

Yang Shen et al. [3] present a framework to deblur the blurry frame in a video clip. They proposed a framework to deblur the motion blurring objects which move fast in the video. This method could not be used in blurry frame with large kernel. Two reasons lead to bad result, one is that the alpha matting algorithm could not get accurate alpha matte of serious blurring object, the other is that the noise is serious in large blurry object, so it becomes hard to restore the latent object accurately.

Hiroyuki Takeda et al. [4] propose a fully 3-D deblurring method is to reduce motion blur from a single motion-blurred video to produce a high-resolution video in both space and time. It is less efficient if the exposure time is not known.

Yu-Wing Tai et al. [5] propose a novel approach to reduce spatially varying motion blur using a hybrid camera system that simultaneously captures high-resolution video at a low-frame rate together with low-resolution video at a high-frame rate. However, this technique is limited to within the low-resolution PSF estimated from optical flows.

Dong-Bok Lee et al. [6] presents a novel motion deblurring algorithm in which a blurred frame can be reconstructed utilizing the high-resolution information of adjacent unblurred frames in order to avoid visually annoying artifacts due to those blurred frames. The blur kernel estimation and deconvolution processes are iteratively performed for the deblurred frame. However, this method is not efficient in case when the blur kernel is shift-variant.

Stanley H. Chan et al. [7] presents a fast algorithm for restoring video sequences. The proposed algorithm does not consider video restoration as a sequence of image restoration

problems. Rather, it treats a video sequence as a space-time volume and poses a space-time total variation regularization to enhance the smoothness of the solution. An augmented Lagrangian method is used to handle the constraints, and an alternating direction method (ADM) is used to iteratively find solutions of the subproblems. However, for large area geometric distortion, non-rigid registration is needed.

Haichao Zhang et al. [8] presents a robust algorithm for estimating a single latent sharp image given multiple blurry and/or noisy observations. The underlying multi-image blind deconvolution problem is solved by linking all of the observations together via a Bayesian-inspired penalty function which couples the unknown latent image, blur kernels, and noise levels together in a unique way. However, it is less effective for non-uniform video deblurring.

III. PROPOSED APPROACH

The proposed system consists of registration of burst of images and Feature detection and extraction using Scale Invariant Feature Transform method and the Fourier burst accumulation algorithm for deblurring the video along with the noise removal and reconstruction.

A. Conversion of video into frames

The video is converted into frames using video reader function in matlab. Here video is taken as input and frames are obtained as output. For video data, file format refers to container format or codec. The video reader function is used to read the video files. It recognizes the container format such as avi, mpeg etc and access codec associated with the particular file. The number of frames in the video file is detected and then the frame is read. Each frame of the video file is converted into the image file.

B. Feature detection and extraction using Scale Invariant Feature Transform

The burst of images are taken as input and SIFT feature detection is followed to register the images. The process of aligning two or more images of the same scene by taking one image as the reference image and the other image as fixed image is called as the image registration. The transformations are done to align with the reference images. The objects contain interesting points called as features. Features are extracted to provide description to the object. The set of features are provided by the SIFT features that are not affected by rotation and object scaling.

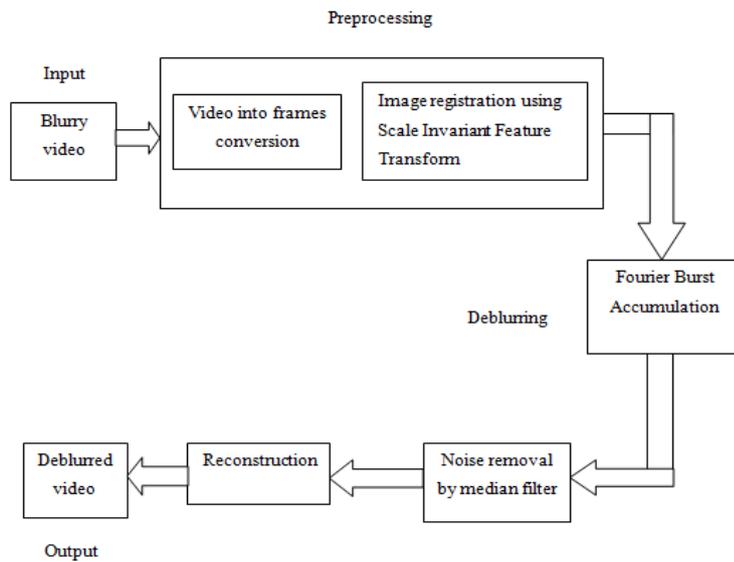


Fig. 1 System Architecture

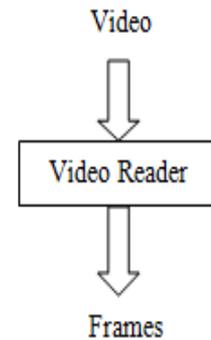


Fig.2 Conversion of video into frames

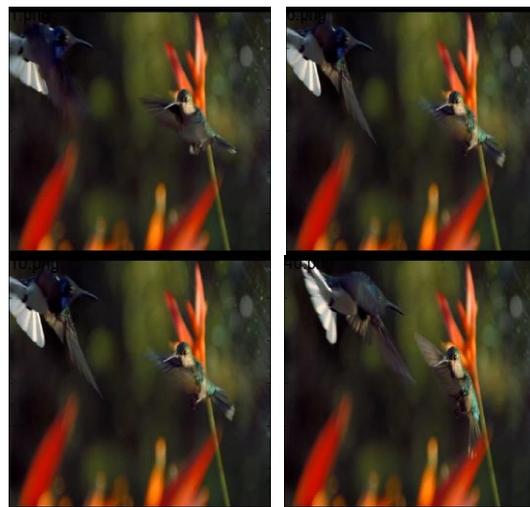


Fig. 3 Video Frames of humming bird video sequence

The Scale Invariant Feature Transform algorithm contains four steps to extract the features :

- Detecting Scale Space Extrema :

In this stage the filtering is done to identify locations and scales from different views of same object. The function used to achieve this is called scale space function .The stable keypoint locations are detected by using Difference Of Gaussian(DOG) technique. The computation is done by finding the difference between two images and it is used to detect the local maxima and minima .Here, each point is compared and if this value is the minimum or maximum then this point is an extrema.

- Localizing the keypoints :

In this stage, more points which have low contrast or poorly localized on an edge are eliminated. The extrema with low contrast is removed by finding the point which has the function value below the threshold value. The large and small

curvature in the difference of Gaussian function is noted. If the difference calculated is low then the keypoint is rejected.

- Assigning the orientation :

The keypoint orientation is found by these steps: The Gaussian smoothed image, the gradient magnitude and orientation is computed and assigned. An orientation histogram is formed from the orientations of sample points. The highest peak in the histogram is used to create a keypoint with that orientation.

- Keypoints Descriptors :

The keypoint descriptors are created by using the gradient data. It is also used to create many histograms centered on the keypoint. The keypoint descriptors contains 128 elements which consist of 16 histograms which can be aligned in 4x4 grid with 8 orientation bins each. The resulting vector are called SIFT keys which are used to identify all the possible objects in an image.



Fig. 4 Feature extraction obtained by scale invariant feature transform

C. *Fourier burst accumulation algorithm:*

The Fourier Burst Accumulation algorithm works as follows: The kernel threshold is set ($k_s=15$) and Fourier transform of the frame is computed. Then the RGB frame is converted into gray scale and the multiple kernel values are obtained. The minimum kernel is found by comparing them with the threshold and finally minimum kernel is the one whose value is less than the threshold. The weights are computed by arithmetically averaging the Fourier magnitude of the channels before the low pass filtering. The fusion itself consists simply of an accumulation of the Fourier coefficients using a higher weight for frequencies with high

magnitude. The algorithm is built on the idea that each image in the burst is generally differently blurred; this being a consequence of the random nature of hand tremor. By doing a weighted average in the Fourier domain, we reconstruct an image combining the least attenuated frequencies in each frame. This algorithm has several advantages. First, it does not introduce typical ringing or overshooting artifacts present in most deconvolution algorithms. This is avoided by not formulating the deblurring problem as an inverse problem of deconvolution. The algorithm produces similar or better results than the state-of-the-art multi-image deconvolution while being significantly faster and with lower memory footprint.



Fig. 5 Frame deblurred by Fourier burst accumulation



Fig. 6 Noise removal by median filter for humming bird video sequence

D. *Noise removal and reconstruction:*

The most effective filter to remove salt and pepper noise is the median filter. It is a non-linear digital filtering technique, often used to remove noise from images or other signals. The idea is to examine a sample of the input and decide if it is representative of the signal. This is performed using a window

consisting of an odd number of samples. The values in the window are sorted into numerical order; the median value, the sample in the center of the window, is selected as the output. The oldest sample is discarded, a new sample acquired, and the calculation repeats. Thus, the noise free images are obtained which are then reconstructed to get the deblurred video.



Fig. 7 The deblurred frames of humming bird video sequence

IV. RESULTS AND DISCUSSION

In order to compute the efficiency of the proposed system, 15 video sequences have been considered. The efficiency is computed based on the coefficient parameters

obtained by noise removal by applying median filter. These coefficients are approximation, horizontal, vertical, and diagonal. According to these coefficients, we found the efficiency by setting the threshold value to 50.

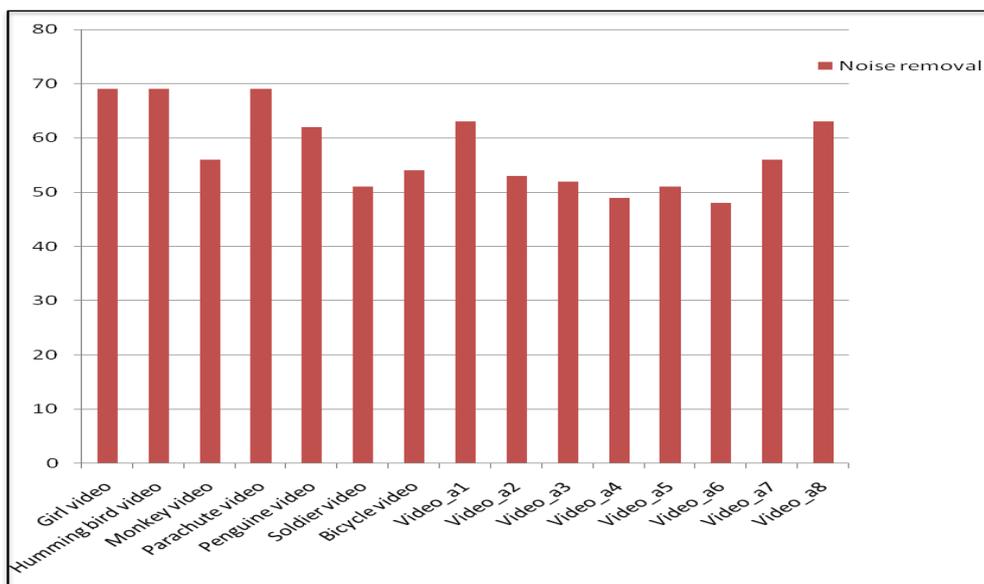


Fig. 8 Graph for deblurring efficiency of the proposed system

From the graph, it can be observed that out of total videos, the noise removal result of only 2 videos is below 50 and the noise removal result of remaining 13 videos is above 50 i.e. the efficient video count to total video count is 87%. Thus, from the table 1, it is found that the overall efficiency of the proposed system is 87%.

V. CONCLUSION AND FUTURE WORK

To improve the efficiency and to overcome the dependency of superpixels which is present in the existing system, video deblurring by Fourier burst accumulation algorithm is proposed. The proposed system has effectively deblurred the video and results showed that the reconstructed

video is sharper and less noisy than the original ones. The proposed system does not introduce typical ringing or overshooting artifacts present in most deconvolution algorithms. This is avoided by not formulating the deblurring problem as an inverse problem of deconvolution. The algorithm produces similar or better results than the state-of-the-art multi-image deconvolution while being significantly faster and with lower memory footprint. Its consistent registration scheme makes the method robust to moving objects. Since the median filter is used for the salt and pepper noise removal, it has effectively removed the noise obtained in the form of coefficient efficiency. The proposed approach can be improved and extended to obtain more fast and enhanced results.

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