

**INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH  
TECHNOLOGY****ENHANCING VIDEO DEBLURRING USING EFFICIENT FOURIER  
AGGREGATION-A REVIEW****Shweta K.Holey<sup>1</sup>,K.V.Warkar<sup>2</sup>**Student<sup>1</sup>,Asst.Professor<sup>2</sup>

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**ABSTRACT**

The goal of video deblurring is to remove the blurriness from blurry videos caused due to camera shake and object motion during exposure. Video deblurring is performed by monitoring videos spatial and temporal changes during video sequences. While most existing algorithms are able to deblur the videos well in controlled environment, they usually fail in the presence of significant variation of the object's motion. There is still a need of better a algorithm for deblurring the videos in an effective manner. We propose a efficient video deblurring technique to handle the blurs due to shaky camera and complex motion blurs due to moving objects. A brief survey of different video deblurring methods available in the literature including analysis and comparative study of different techniques used for deblurring has been done.

**KEYWORDS:** camera shake,deblurring,motion blurs**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. 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. Handheld video capture devices are now commonplace. As a result, video stabilization has become an essential step in video capture pipelines, often performed automatically at capture time (e.g., iPhone, Google Pixel), or as a service on sharing platforms (e.g., YouTube, Facebook).

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 de-blurring 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 shutter 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 in-existent 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. Image and video deblurring has been extensively studied and many proposed methods yielded great success. Although a blurry image can be sharpened by convolution through different point-spread functions or blur kernels, e.g., spatially varying PSFs, restoring a blurry image is inherently an ill-posed problem. While video deblurring can make use of extra information from adjacent frames in the deblurring process, it must also consider additional problems.



## II. LITERATURE SURVEY

There is a rich literature in video deblurring and 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. To identify a suitable sharp superpixel to replace a blurry one, the author enriched the search space with a non-uniform motion blur kernel, and used a generalized PatchMatch algorithm to handle rotation, scale, and blur differences in the matching step. Instead of using pixel-based or regular patch-based representation, a superpixel-based representation is adopted. The non-uniform motion blur kernels are estimated from the motion field of these superpixels, and spatially varying motion model considers spatial and temporal coherence to find sharp superpixels.

Since simply dividing a frame into regular patches may increase matching errors when finding sharp patches from other frames. Here, the SLIC algorithm [30] is used to segment each frame into superpixels. After a frame is segmented into superpixels, estimated a blur kernel for each superpixel and combine the blur kernels of all superpixels to form the spatially varying motion blur kernels. To minimize estimation errors due to severely blurred moving objects, we optimize the blur kernels from neighbor superpixels to find globally smoothed blur kernels. The estimated motion blur kernels serve as the initial blur filter in the superpixel matching step.

PatchMatch-based search strategy based on the original PatchMatch algorithm [10] is presented to search for a sharp superpixel to replace a blurry one using estimated motion model. After the PatchMatch initialization step, iterated through the propagation step and the random search step. A structure-preserving video deblurring algorithm is developed that uses irregular motion-based segmentation to estimate a non-uniform motion model and perform superpixel deblurring. The system assumes that sharp frames or superpixels are sparsely spread in video sequence and uses sharp superpixels to reconstruct blurry ones. Thus the system effectively deals with the reconstruction of blurry frames on both static and moving objects. 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. Traditional methods focus on estimating a single motion blur kernel for the entire image. In contrast, they aim to restore images blurred by unknown, spatially varying motion blur kernels caused by different relative motions between the camera and the scene. The algorithm simultaneously estimates multiple motions, motion blur kernels, and the associated image segments. This algorithm has a few limitations. 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, our 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. Two kinds of motion blurring effects can be removed in the video, one is the blurring effect caused by hand shaking, the other is the blurring effect caused by a fast moving object. For the blurring caused by hand shaking, PSF is estimated by comparing the stable area in blurry frame and non-blurry frame, so the Richardson-Lucy algorithm can restore the blurry frame by non-blind deconvolution. 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. Unlike other existing approaches, the proposed deblurring kernel is free from knowledge of the local motions. Most importantly, due to its inherent locally adaptive nature, the 3-D deblurring is capable of automatically deblurring the portions of the sequence,

which are motion blurred, without segmentation and without adversely affecting the rest of the spatiotemporal domain, where such blur is not present. 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. This work is inspired by Ben-Ezra and Nayar who introduced the hybrid camera idea for correcting global motion blur for a single still image and broaden the scope of the problem to address spatially varying blur as well as video imagery. They have proposed an approach for image/video deblurring using a hybrid camera. This approach can produce results that are sharper and cleaner than state-of-the-art techniques. 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. First, a motion-compensated predictor for the blurred frame is derived from its neighboring unblurred frame via specific motion estimation. Then, an accurate blur kernel, which is difficult to directly obtain from the blurred frame itself, is computed using both the predictor and the blurred frame. Next, a residual deconvolution is applied to both of those frames in order to reduce the ringing artifacts inherently caused by conventional deconvolution. 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, as opposed to existing methods, 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. The optimization problem is solved by transforming the original unconstrained minimization problem to an equivalent constrained minimization problem. 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. The proposed algorithm has a wide range of applications, including video deblurring and denoising, disparity map refinement, and reducing hot-air turbulence effects. 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. The resulting algorithm, which requires no essential tuning parameters, can recover a high quality image from a set of observations containing potentially both blurry and noisy examples, without knowing a priori the degradation type of each observation. Experimental results on both synthetic and real-world test images clearly demonstrate the efficiency of the proposed method. However, it is less effective for non-uniform video deblurring.

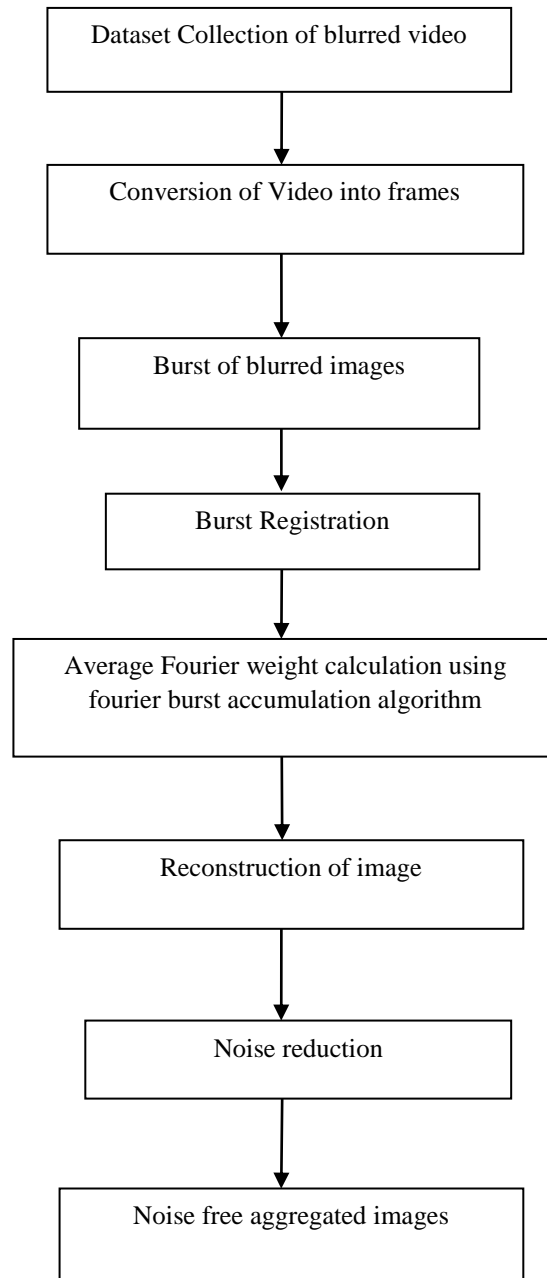
### III. PROPOSED APPROACH

In this work, we present Fourier burst accumulation algorithm that removes blur due to camera shake by combining information in the Fourier domain from nearby frames in a video. The dynamic nature of typical videos with the presence of multiple moving objects and occlusions makes this problem of camera shake removal extremely challenging, in particular when low complexity is needed.

Given an input video frame, we first create a consistent registered version of temporally adjacent frames. Then, the set of consistently registered frames is block-wise fused in the Fourier domain with weights depending on the Fourier spectrum magnitude.

In the proposed system, burst of images are taken into account where each image is blurred differently. The weighted average in the Fourier domain is performed for each image. Reconstruction of an image is done by combining the least attenuated frequencies in each frame. It does not introduce typical ringing or overshooting

artifacts present in most deconvolution algorithms. Noise reduction is done at the last to obtain sharper and noise free image.



*Fig 1 : Flow of Proposed Approach*

*Table 1. Comparative analysis of different techniques used for video deblurring*

No.	Techniques/Algorithm	Advantages	Limitations
1.	Patch-match algorithm a superpixel-based representation is adopted.[1]	It effectively deals with the reconstruction of blurry frames on both static and moving objects.	It fails if no sharp superpixels can be found from other frames of the video
2.	Richardson-Lucy algorithm is used.	Effectively deblur the motion blurring objects which move fast in the video.	This method could not be used in blurry frame with large kernel.
3.	Fully 3-D deblurring method is proposed.	It is capable of automatically deblurring the portions of the sequence, which are motion blurred, without segmentation	It is less efficient if the exposure time is not known.
4.	A approach to reduce spatially varying motion blur using a hybrid camera system is adopted.	It produces results that are sharper and cleaner than state-of-the-art techniques.	It is limited to within the low-resolution PSF estimated from optical flows
5.	A novel motion deblurring algorithm is used.	It provides superior deblurring over conventional deblurring algorithms.	It is not efficient in case when the blur kernel is shift-variant.
6.	An augmented Lagrangian method and an alternating direction method (ADM) is used.	It solves video restoration problems.	It is less effective for large area geometric distortion, as the non-rigid registration is needed.
7.	A robust algorithm for estimating a single latent sharp image is presented	It is efficient for both synthetic and real-world test images.	It is less effective for non-uniform video deblurring.

#### IV. OBJECTIVES OF THE PRESENT WORK

The objectives of the proposed approach are best described as below:

1. To collect the dataset, video to frame conversion and applying preprocessing steps to frames.
2. To handle complex blurs due to moving objects.
3. To remove noise and blurriness from blurry images.
4. To improve the analysis and accuracy.

#### V. CONCLUSION

A brief survey of different video deblurring methods available in the literature including analysis and comparative study of different techniques used for deblurring is done. To improve the efficiency and to overcome the problem of existing system, Fourier aggregation using a Fourier burst accumulation algorithm is discussed.

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