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A Research on -A Novel approach for Feature Detection and Extraction using Scale Invariant Feature Transform

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Abstract — *The goal of video deblurring is to remove the blurrness 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.The first step is the conversion of blurry video into frames for futher processing. In this paper,a robust approach for burst registration and feature detection and extraction using Scale invariant feature transform algorithm which is not affected by rotation and object scaling is proposed.*

Keywords- *camera shake,deblurring,motion blurs,feature extraction*

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 friends 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.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.

Video deblurring is an important research interest for many years covering widespread application in diverse disciplines. It plas a critical role in numerous applications such as video survelliance,photography,biomedicine,astronomy.Even though much progress has been made in recent years, it is still a challenging problem to develop an efficient algorithm for video deblurring caused due to camera shake and complex motion blur.Over recent years, much research has been devoted to video deblurring.Even though the motion blur from camera shake is still a major problem in videos captured by hand held devices. Shaky cameras often capture videos with motion blurs, especially when the light is insufficient.This phenomenon however, significantly increases the difficulty of video deblurring. Motivated by the effectiveness of fourier agreegation,enhanced video deblurring which not only will handle blurs caused by a shaky camera, but also complex blurs due to moving objects will be proposed.

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. 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 superpixelbased 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.

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 imageThis 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.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 fora single still imageand 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 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. 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

The proposed system consists of registration of burst of images and Feature detection and extraction using Scale Invariant Feature Transform method.

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.

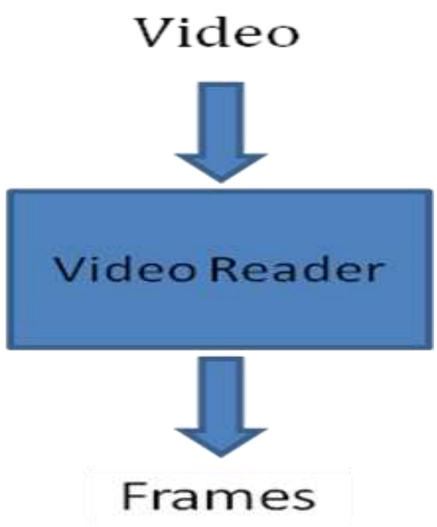

Fig 1. Conversion of video into frames

Fig 2.Frames obtained from video 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.

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.

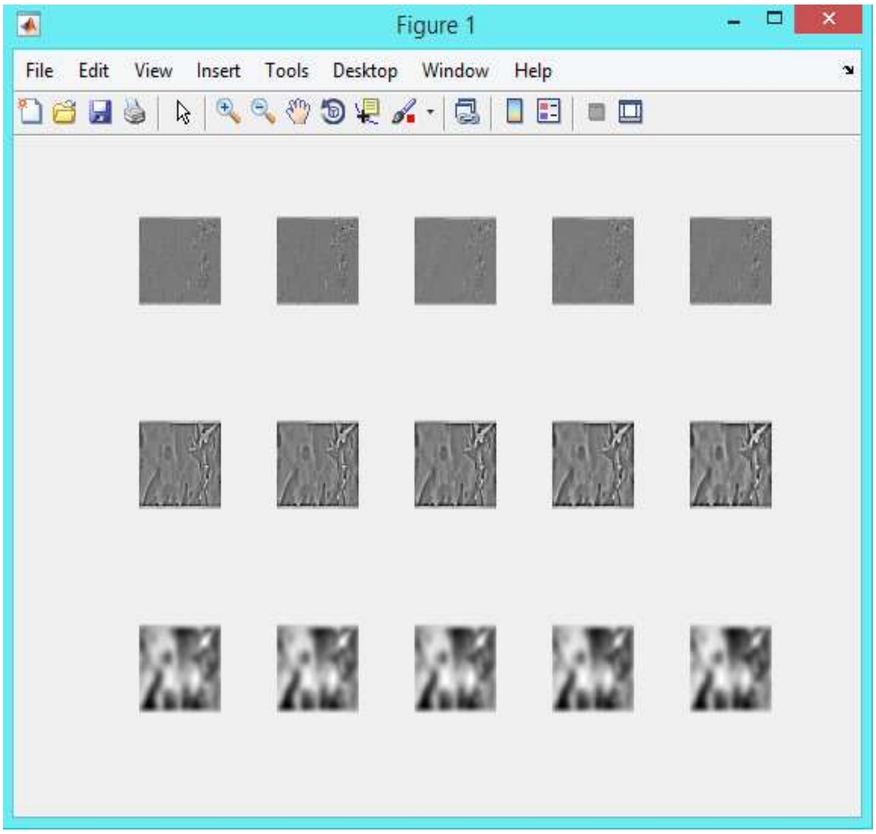

Fig 3. Applying Scale invariant Feature Transform algorithm on blurry frame

- 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.

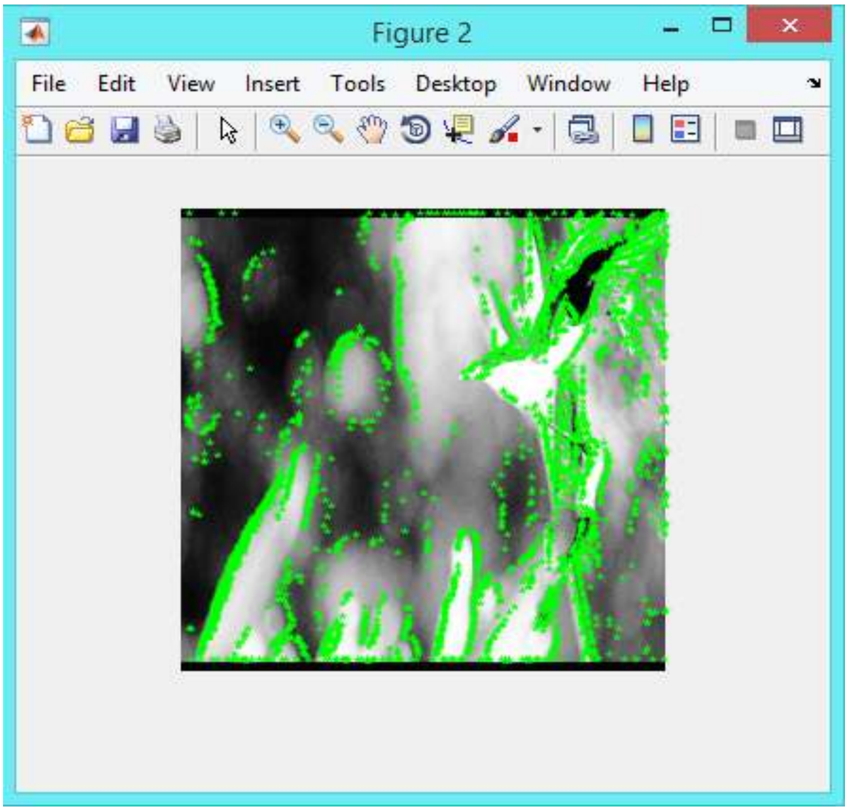

Fig 4: Features are detected and extracted using Scale invariant feature transform

IV. CONCLUSION AND FUTURE WORK

To improve the effectiveness of deblurring a video and to overcome the problem of complex motion deblurring in absence of the sharp superpixels from other frames of the video ,Feature detection and extraction using Scale Invariant Feature Transform algorithm is proposed.

Proposed system has effectively registered the burst of images and features are detected and extracted from the blurred frames with Scale invariant feature transform that is not affected by rotation and object scaling.In future work,the removal of blurriness from blurred frames of video will be done using fourier burst accumulation algorithm.

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