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Review of Local Subspace Video Stabilization Using Signature Value Decomposition Method

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ABSTRACT: Video stabilization is an important step for many video processing, so by stabilizing video we enhance video quality by stabilizing unstable motion. The main aim of digital video stabilization is to get rid of unwanted movements, undesirable jiggle, blur and poor quality video. Many video stabilization techniques hence are developed with different algorithms & methods. The paper presents the review of a new video stabilization method that simultaneously factors and smoothens motion trajectories. The paper focuses on the trajectories with a time-variant local subspace constraint. In every column of trajectory matrix is factored and smoothed in separate local subspace with the help of signature value decomposition. Model makes our method more flexible and accurate than subspace video stabilization. By designing a novel outlier detection technique which can help in find out the relationship between consecutive local subspace by value decomposition. The stabilized video is achieved by applying factorization on synthesis data and finally outlier detection with subspace transform is done and we get stabilized video. Using video stabilization quality standards such as PSNR & ITF, we can plot graph and assess the proposed algorithm.

KEYWORDS: Feature point extraction, Matrix factorization, Video stabilization, Local subspace constraint.

I. INTRODUCTION

The video processing have become increasingly important with increasing popularity of many applications such as hand held devices like camcorders, smart phone cameras, digital cameras, surveillance systems, unmanned aerial vehicle (UAV) systems. Thus, it is inevitable presence of some unwanted motion effects, blur, and jitter in videos taken by hand or from mobile platforms. Hence it is desirable to apply digital video stabilization algorithm in order to acquire good quality video to get rid of undesirable motion.

Video stabilization deals with object Motion and camera motion which are two main sources of dynamic information in videos. Camera motion comprises of pan, zoom, tilt and/or combination of these basic components which is also referred as global motion. Whereas object motion is considered as movement of objects in a scene also referred as local motion.

II. RELATED WORK

Video stabilization is video enhancement technique which aims at removing misalignment of video frames and unwanted motions or vibrations in the captured video sequence. Researchers have developed many video stabilization algorithms. Stabilization of video is done for 2D, 2.5D,3D motion models and for compressed video streams such as MPEG, MPEG-2, H.264 or MPEG-4. Matsushita et al.[11], proposed direct pixel based full frame video stabilization method with motion in painting. They used affine motion model for estimation and the Gaussian kernel filtering was used to smoothen camera motion. Motion estimation is the base of any video stabilization algorithm. A fast video stabilization technique was explored by Ko et al. [12] in which gray coded bit-plane matching algorithm was used which estimates local and global motion vectors.

Battiato et al. [13] proposed a robust block-based image/ video registration approach for mobile imaging devices. Using some simple rejection rules estimated Interframe camera transformation parameters from local motion vectors. In this registration approach they used motion estimator, filters and error matrix to stabilize video frames. They tested their work on ARM device and achieved stabilized video sequence for the real time performance. Cai et al.[2] explored

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camera motion estimation algorithm using histograms of local motions for mobile platforms. They considered highest peak in each histogram of local motions.

Okade et al. [14] proposed a novel compressed domain framework for video stabilization which was fast and robust. In comparison to the existing pixel based stabilization techniques. Further they utilized wavelet analysis to estimate the camera motion parameters from block motion vectors. This method was efficient and better in case to avoid computational complexity. Rawat and Singhai [10] developed adaptive motion smoothening method for removing high frequency jitters. This method stabilizes worst and large motion videos where multiple moving objects are present in the scene. Manish Okade et.al [16] proposed robust learning based camera motion characterization scheme for video stabilization. They carried out experimental validation using exhaustive search motion estimation obtained block00 motion vectors as well as H.264/AVC and reduced processing time for stabilizing video sequence.

Buehleretal.[2001],insteadbeginsbycomputinga3Dmodelofthe input camera motion and scene. Image-based rendering techniques can then be used to render novel views from new camera paths for video so static scenes [Fitzgibbonetal.2005; Bhatetal.2007]. Dynamic scenes are more challenging, however, since blending multiple frames causes ghosting. Zhang et al. [2009] avoid ghosting by fitting a homography to each frame; this approach cannot handle parallax, however. Liu et al. [2009] introduced content-preserving warps as a nonphysically realistic approach to rendering the appearance of new camera paths for dynamic scenes.

Wang et al. [13] represent each trajectory as a B´ezier curve. They formulate video stabilization as a spatial temporal optimization problem that finds smooth trajectories as well as preserves offsets of neighboring curves. GoldsteinandFattal[3]avoid3Dreconstructionbyusing‘epipolar transfer’ to construct and smooth virtual trajectories.

Liu et al. [2009] introduced content-preserving warps as a nonphysically realistic approach to rendering the appearance of new camera paths for dynamic scenes. In this method, the reconstructed 3D point cloud is projected to both the input and output cameras, producing a sparse set of displacements that guide a spatially varying warping technique.

III. VIDEO STABILIZATION

The Video stabilization can either be achieved by hardware or post image processing approaches which are described as below:

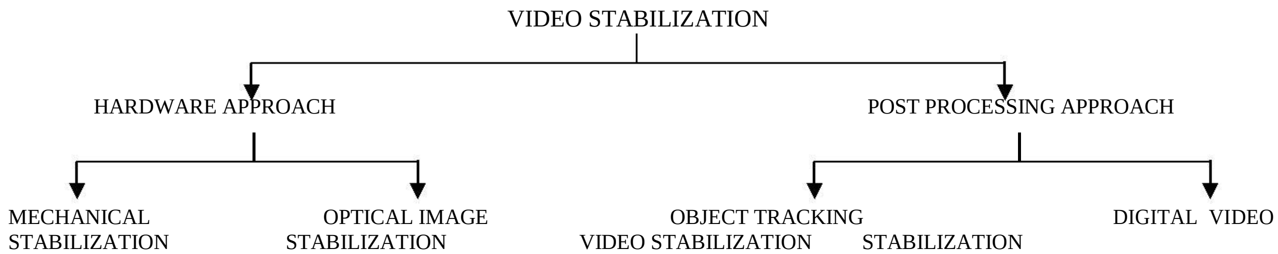

Fig 1: Video Stabilization Approaches

A. Hardware Approach

I. MECHANICAL STABILIZATION

In the first category we use hardware motion sensors or mechanical devices such as gyros, accelerometers and mechanical dampers. Thus instead of holding camera in hand, mechanical stabilizers such as tripod, Steadicam are used which reduce platform vibration and in turn provide stabilization. [1]

II. OPTICAL IMAGE STABILIZATION

In optical image stabilization(OIS) CCD/CMOS sensors, microcontrollers, Hall sensors are used. Optical stabilization is much expensive than digital technique but its computational complexity is low as it is concerned with light rays falling on the camera’s lens.[1] In these approaches detection and correction steps are applied before acquisition so as to avoid post processing computation.

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B.Post Image Processing Approach

I.OBJECT TRACKING VIDEO STABILIZATION

The second category is of object tracking [2, 3]where objects such as person, vehicle, and road signs are the targets to track. This is also known as video tracking. The objective of video tracking is to associate target objects in consecutive video frames.

II. DIGITAL VIDEO STABILIZATION

This is the estimation based approach. In this category, a video stabilization pipeline usually comprises three stages: motion estimation, motion smoothing, and motion compensation [5].In this paper, we will review these stages of video stabilization and different approaches related to it.

IV. SUBSPACE VIDEO STABILIZATION

Visual tracking is a very important and challenging task. The most common situation in visual tracking is to work with a perspective camera. In general, the motion trajectories from a perspective camera will lie on a nonlinear manifold instead of a linear subspace [8]. However, it is possible to approximate the manifold locally (over a short period of time) with a linear subspace.

In our subspace approach to video stabilization consists of four steps. First, we have to use standard 2D point tracking and assemble the 2D trajectories of sparse scene points into an incomplete trajectory matrix. Second , we can perform moving factorization to efficiently find a time-varying subspace approximation to the input motion that locally represents the trajectories as the product of basis vectors are also called as eigen-trajectories and a coefficient matrix that describes each feature as a linear combination of these eigen-trajectories. Third, we perform motion planning (or smoothing) on the eigen-trajectories, effectively smoothing the input motion while respecting the low rank relationship of the motion of points in the scene. Fourth, the eigen-trajectories are remultiplied with the original coefficient matrix to yield a set of smoothed output trajectories that can be passed to a rendering solution such as content-preserving warps [Liuetal. 2009], to create a final result. Most video stabilization methods track a set of feature points through a video in the first step.

V. FEATURE POINT EXTRACTION

A feature is an interesting part of an image. Features are used as a starting point for many computer vision algorithms. As features are used as the starting point and main primitives for subsequent algorithms, the overall algorithm will often only be as good as its feature detector. Consequently, the desirable property for a feature detector is repeatability; whether or not the same feature will be detected in two or more different images of the same scene.

Feature detection is a low-level image processing operation. It is usually performed as the first operation on an image, and examines every pixel to see if there is a feature present at that pixel. If this is part of a larger algorithm, then the algorithm will typically only examine the image in the region of the features. As a built-in pre-requisite to feature detection, the input image is usually smoothed by a Gaussian kernel in a scale space representation and one or several feature images are computed, often expressed in terms of local image derivatives operations. When feature detection is computationally expensive and there are time constraints, a higher level algorithm may be used to guide the feature detection stage, so that only certain parts of the image are searched for features.

Once features have been detected, a local image patch around the feature can be extracted. This extraction may involve quite considerable amounts of image processing. The result is known as a feature descriptor or feature vector. Among the approaches that are used to feature description, one can mention N-jets and local histograms (see scale-invariant feature transform for one example of a local histogram descriptor). In addition to such attribute information, the feature detection step by itself may also provide complementary attributes, such as the edge orientation and gradient magnitude in edge detection and the polarity and the strength of the blob in blob detection.

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VI.PROPOSED SYSTEM

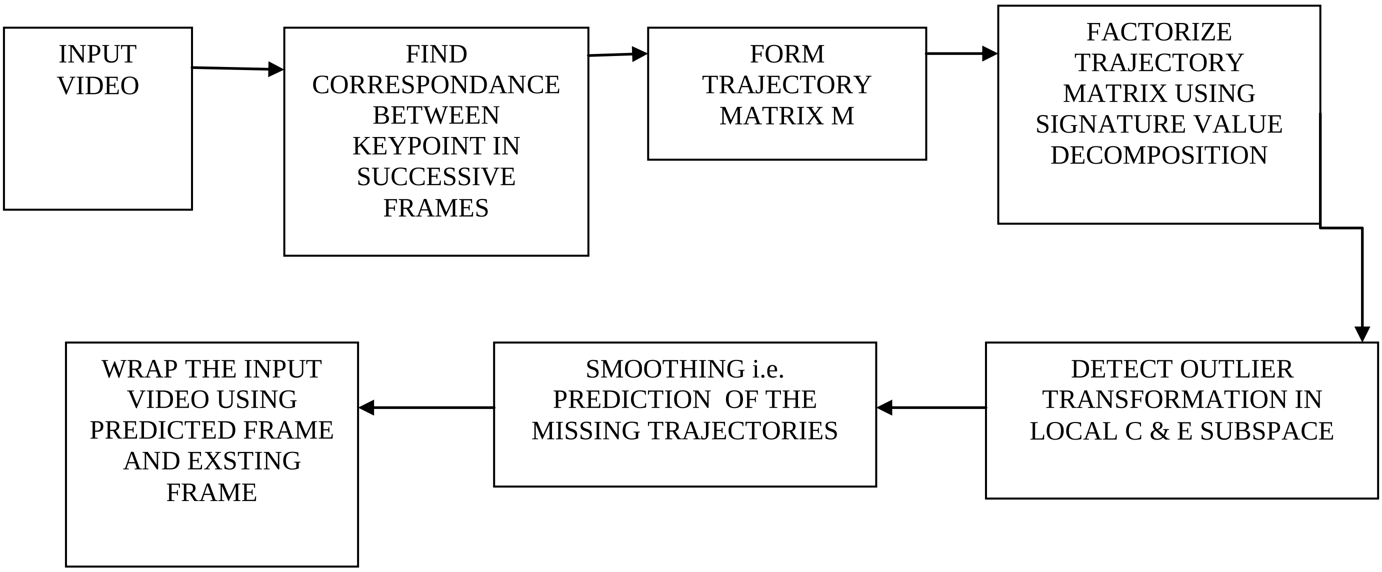

Fig.2. Block diagram of proposed system.

1. Track 2D motion trajectories in an input video and assemble them into a matrix M.
2. Factor and smooth columns of M in local subspace using (6)-(9). The first k columns of M are smoothed in a same subspace as in (7); the last k columns are processed in a similar way; and every other column is smoothed in separate local subspace as in (9).
3. Before factoring for every local subspace, detect outliers using the method in [8]. After local factorization in every local window, detect and handle outliers using subspace transform based technique as in (10)-(13).
4.Warp the input video guided by the correspondence between M using content preserve warping

VII. LOCAL SUBSPACE CONSTRAINT

The subspace constraints are geometrically meaningful and are not violated at depth discontinuities or when the camera motion changes abruptly. Furthermore, we show that the subspace constraints on flow fields apply for a variety of imaging models, scene models and motion models. Hence, the presented approach for constrained multi-frame flow estimation is general. However, our approach does not require prior knowledge of the underlying world or camera model. Although linear subspace constraints have been used successfully in the past for recovering 3D information, it has been assumed that 2D correspondences are given. However, correspondence estimation is a fundamental problem in motion analysis. In this paper, we use multi-frame subspace constraints to constrain the 2D correspondence estimation process itself, and not for 3D recovery. the set of all flow fields in a sequence of frames imaging a rigid scene resides in a low-dimensional linear subspace. Based on this observation, we develop a method for simultaneous estimation of optical flow across multiple frames, which uses these subspace constraints. The multi-frame subspace constraints are strong constraints, and they replace commonly used heuristic constraints, such as spatial or temporal smoothness.

Motion trajectories captured by a perspective camera lie on a non-linear manifold instead of a linear subspace . This manifold can be approximated with several linear subspaces locally. In subspace video stabilization, this property is assumed to be held over a short window of frames, and this window is at least as large as the filter kernel. However, Liu et al. still factor and smooth the trajectory matrix in a single global subspace as in . For the entire trajectory matrix, their global subspace constraint is over strict. Many correct trajectories are detected as outliers and removed after moving factorization. These correct trajectories' factorization error exceeds a threshold (Liu et al. set the threshold to 3 pixels) because the global subspace constraint cannot fit the manifold well. In our work, we use multiple local

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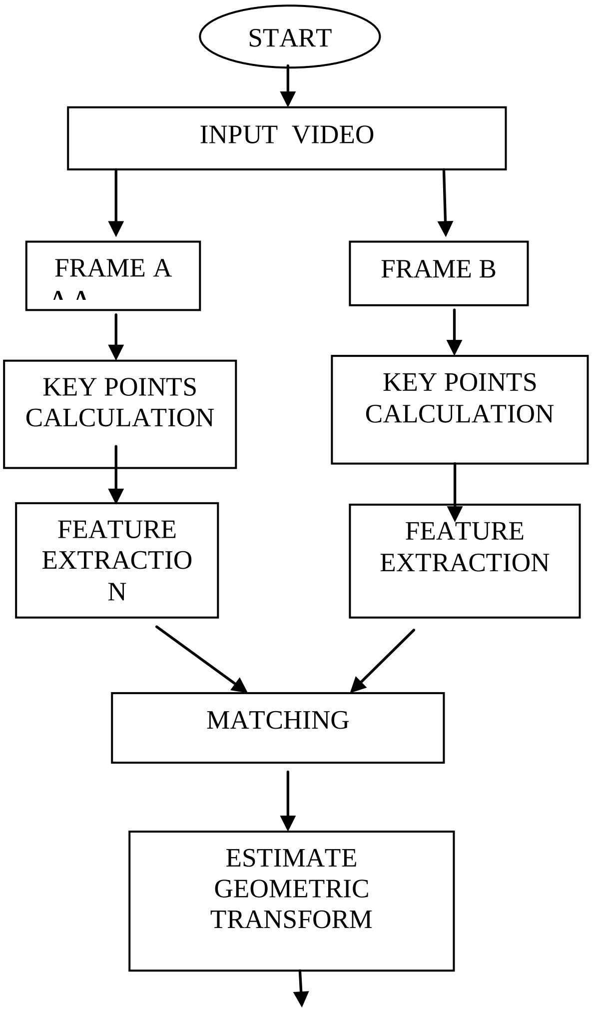
subspaces rather than a single global subspace. This time-variant model is more flexible. Different from subspace video stabilization, we do not require the coefficient matrix fixed. The low-rank representation of a trajectory varies in different local subspaces as in which gives a better approximation to the non-linear manifold.

For video stabilization, factorization should be accurate for both tracked trajectories and extended segments. In real videos, there is no access to the missing data of a trajectory matrix. So we randomly generated 500 points within a 100×100×100 cube, and synthesized a sequence of 300 frames (the size of these frames are 600×600) by a moving perspective camera. The focal length of the camera was set to 500 and rotation angles changed from$-\pi/4$ to $+\pi/4$. Then we added gaussian noise (σ =3and μ =0) to every captured point in synthesized frames. The factorization window size and moving step of moving factorization were set to 50 and 5, which were the same as in [8]. The factorization window size of our local factorization was 51. Since the synthetic sequence was captured by a perspective camera, we settherank r to9. These parameters were also used in experiments on real videos,but we did not employ outlier detection because the synthetic sequence was free from outliers. After factoring the synthesized trajectory matrix by moving factorization (MF) and our local factorization (LF), we compared their factorization error on both captured and extended points.

For extended points, our method is also much more accurate than moving factorization. The average error on extended points is 0.7076 pixels by our method, which is about half of the error 1.4743 pixels by moving factorization. It is because our method better approximates the non-linear manifold using local subspace constraint.

VIII.PROPOSED ALGORITHM



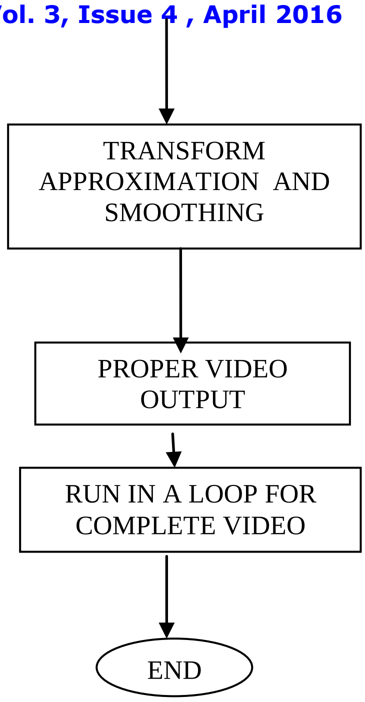


Fig.3 Flowchart

IX.CONCLUSION

In this paper, the review of the different approaches and techniques of video stabilization are discussed. The paper revealed the basic stages such as trajectory motion detection, feature point extraction, local subspace constraint ,subspace video stabilization. Different categories of motion estimation such as pixel based and feature based motion estimation method are discussed. It smooths every column of a trajectory matrix in separate local subspace. By utilizing the local subspace constraint, our factorization is more accurate than moving factorization These algorithms contain different flow of execution and can be applied for different types of video sequences. It also preserves more points for content preserving warps, which is crucial to the quality of stabilized videos. a novel outlier detection technique that utilizes the relationship between consecutive local subspaces, and it can reject the outliers that fail subspace video stabilization while maintain computational efficiency. The experiments show that our method not only out performs subspace video stabilization but also is comparable with some other state-of-the-art methods.

In future scope, speed of acquiring motion trajectories and reduction in calculations are the parameters to be emphasized.

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