



Video Stabilization Technique and Performance Assessment

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ABSTRACT: The objective of video stabilization is to remove the unwanted camera motion and obtain stable versions. In this paper we present video stabilization algorithm by using only L1 optimization method and mixed L1-L2 optimization method. After applying both methods we compared results of both method. Mixed L1-L2 optimization algorithm used for removing unwanted camera movements as well as keeping original video information at greatest extent.

KEYWORDS: video stabilization, mixed L1-L2 optimization

I. INTRODUCTION

Handheld or vehicle mounted cameras often lead to shaking videos, which usually have low visual quality and are not suitable for some post process such as object detection and tracking. Video stabilization is a technique that aims to reduce or remove unwanted camera motion to obtain more stable videos. Some handheld cameras are significantly lighter, resulting in low quality video with jitters. The same problem occurs when the camera mounted on vehicle with unstable motion, such as unmanned aerial vehicle (UAV). Video stabilization is applied to remove handshaking problem in order to improve the visual quality of these videos. Video stabilization algorithm in general consist of three main steps: 1) Original camera path estimation, 2) Smooth camera path computation and 3) Synthesizing the stabilized video. Different method differ in three steps. Among many stabilization algorithms, Grundmann's L1 camera path optimization method [1] and Hui Qu, Li Song mixed L1-L2 optimization method[2]. In this paper we are using mixed L1-L2 optimization method for that we go through five major steps i.e. we can say algorithm for mixed L1-L2 optimization method. Original camera path estimation is first step of video stabilization. Feature tracking and 2D linear models to compute the 2D camera path or use structure form motion like Liu et al [3] to estimate the 3D camera path. The 2D method is computationally efficient while the 3D camera path is more accurate at expense of computation complexity. Smooth camera path estimation removes high frequency jitters and computes global transformation necessary to stabilize the current frame. Grundmann et al [1] used L1 smoothness constraint based on cinematography principles to obtain optimal camera path, which lead to good stabilization results, but discard much original video information. Synthesizing the stabilized video using transformations obtained in smooth camera path estimation is last step of video stabilization. Many methods just keep central parts of original frames to achieve better visual quality. However, further post processing, e.g. inpainting, can be applied to obtain full frames. After studying work[1,2] we implemented a mixed L1-L2 optimization for 2D video stabilization, which can not only achieve good stabilized video, but also retain as much as information of original video as possible. By adjusting only one parameter, users can control the degree of stabilization and fidelity of original video as needed.

The rest of paper is organized as follows. We introduce work flow of algorithm in section 2 Grundmann's work briefly in section 3 and then presents mixed L1-L2 model for video stabilization in section 4 and then calculation of PSNR in section 5. Experiments are shown in section 6 to demonstrate the performance of algorithms and conclusion in section 7. In section 8 Acknowledgment, in section 9 Reference.

II. PROPOSED ALGORITHM

In step 1, we track features by pyramidal Lucas-Kanade like Grundmann et al, but we perform global outlier rejection by RANSAC. To improve the accuracy of outlier rejection, we set a minimum distance between features to ensure the distribution of selected features is relatively uniform on the whole frame. Besides, we re-select features for tracking every 10 frames to reduce the accumulated error of tracked features.

In step 2, we perform motion modelling and compute original Camera path. We need to find original camera path for determining the unintentional camera path.

In step 3, the problem has inclusion and proximity constraints, which are the same as those in L1 optimization method. So we implement mixed L1-L2 optimization method to remove the drawbacks of simple L1 method.

In step4, homography is used to replace similarity in some frames to suppress rolling shutter effects due to its higher accuracy on modelling inter-frame motions. However, homography is unstable and the replacement should be carefully controlled. We use the similar method as Grundmann.

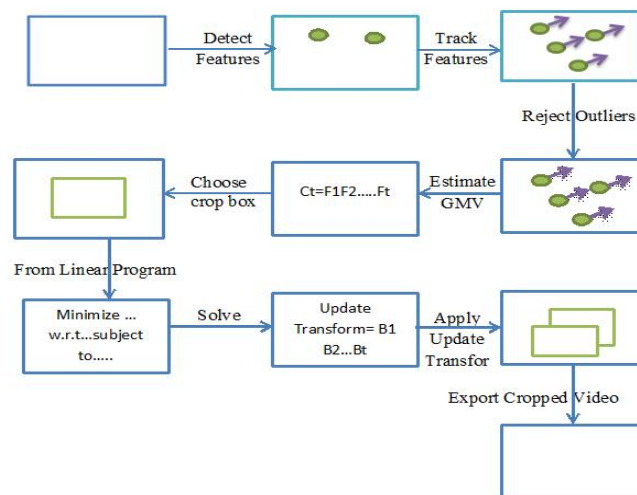


Fig.1. proposed algorithm schema

From fig. 2 to fig. 7 shows the actual results of implementation of our proposed algorithm.



Fig.2 represents two consecutive frames for comparison we named those frame as frame A and Frame B.



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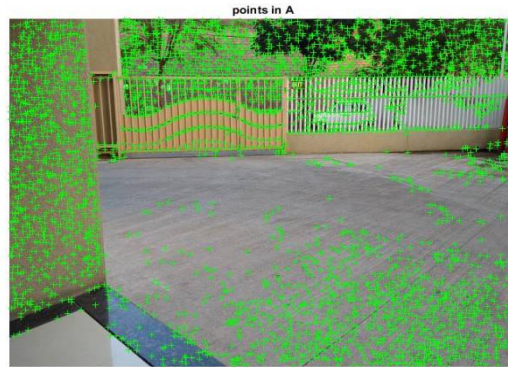


Fig.3 shows feature points extracted in Frame A.

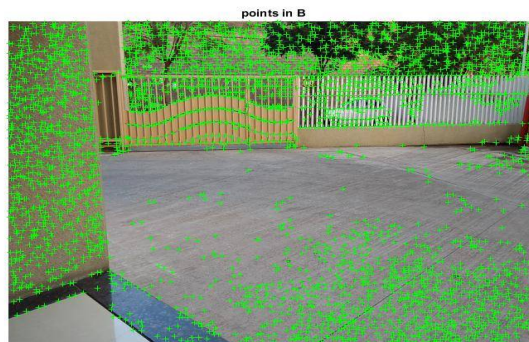


Fig.4 shows feature point extracted in Frame B.

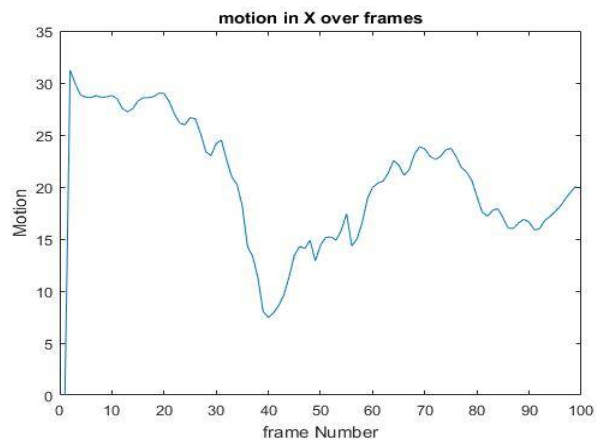


Fig.5 shows the motion of extracted points from Frame A & B over X frames.

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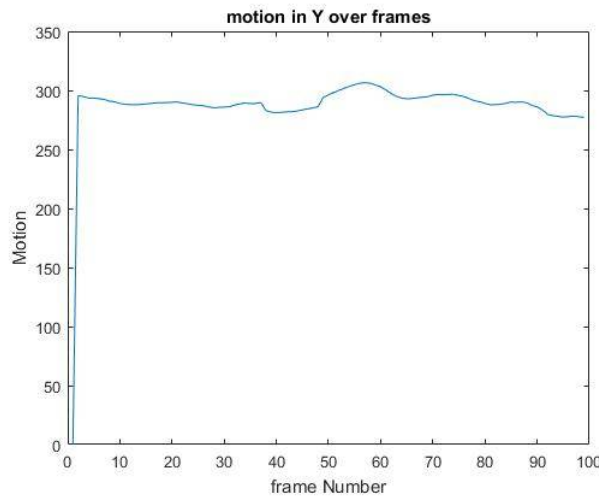


Fig.6 shows the motion of extracted points from Frame A & B over Y frames.

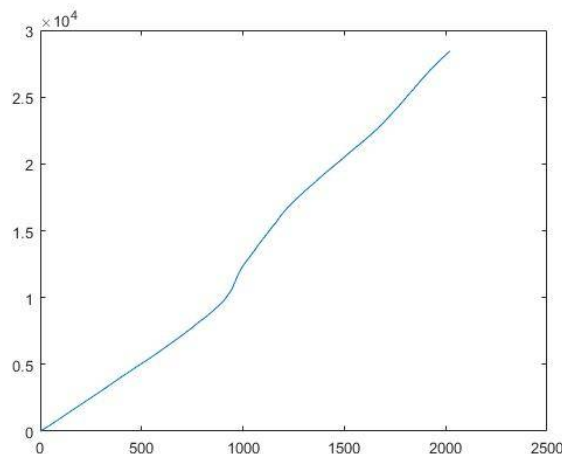


Fig. 7 shows the motion of X and Y points with respect to each other.

III. L1 OPTIMIZATION METHOD FOR VIDEO STABILIZATION

From a cinematographic standpoint, the most pleasant viewing experience is conveyed by the use of either static cameras, panning ones mounted on tripods or cameras placed onto a dolly. Changes between these shot types can be obtained by introduction of cut or jerk-free transition, i.e. avoiding sudden changes in acceleration. We want to compute camera path $P(t)$ to adhere these cinematographic characteristics, but choose not to introduce additional cuts beyond the ones already contained in the original cuts beyond the ones already contained in original video

For the camera path $C(t)$ of the original video footage has been computed (e.g. from feature tracks) and is described by parametric linear motion model at each instance of time. Let the video be a sequence of images I_1, I_2, \dots, I_n , where each frame pair (I_{t-1}, I_t) is associated with a linear motion model $F_t(x)$ modelling the motion of feature points x from I_t to I_{t-1} . The original camera path C_t is defined as

$$C_{t+1} = C_t F_{t+1} \Rightarrow C_t = F_1 F_2 \dots F_t \quad (1)$$



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Vol. 6, Issue 5, May 2017

With C_t , they expressed the desired optimal path P_t as

$$P_t = C_t B_t \quad (2)$$

Where B_t is the update transform that stabilizes the corresponding frame. The objective function of their L1 optimization problem is

$$O(P) = \omega_1 \|D(P)\| + \omega_2 \|D^2(P)\| + \omega_3 \|D^3(P)\| \quad (3)$$

Where $\omega_1, \omega_2, \omega_3$ are empirical weights and D means derivative. The relative values of $\omega_1, \omega_2, \omega_3$ are crucial to the smoothed camera path and should be carefully set. They inclusion constraint is added to preserve the intent of video. Finally, Grundmann's transformed the original frames by B_t and retain the content within a crop window, thus the stabilized video has no blank areas but discard some information on boundary of the original video.

This algorithm is effective for variety of videos, however it discards information due to cropping, which may not be suitable for videos with important information near boundary. Three parameters in equation $\omega_1, \omega_2, \omega_3$ are empirically set and hard to be adaptable to different kinds of videos.

IV. MIXED L1-L2 OPTIMIZATION METHOD FOR VIDEO STABILIZATION

L1 optimization has some drawbacks like this method discards information due to cropping i.e. not suitable for video with important information near boundary, other disadvantage is $\omega_1, \omega_2, \omega_3$ are empirically set which is hard to be adaptable to different kinds of video.

L1 optimization has a property of sparsity, making the computed optimal path has derivatives exactly zero for most segments, while L2 optimization is to achieve the best estimation in least square sense. In order to keep boundary information of original videos as much as possible while performing video stabilization, we expect that optimal camera path is close to original camera path, which can be realized by the introduction of a L2 term in objective function

$$O(P) = L1(P) + \lambda \|P - C\|_2 \quad (4)$$

Where $L1(P)$ is the L1 term similar to that in equation $\omega_1 = \omega_2 = \omega_3 = 1$, λ is a weight to adjust the smoothness of the path.

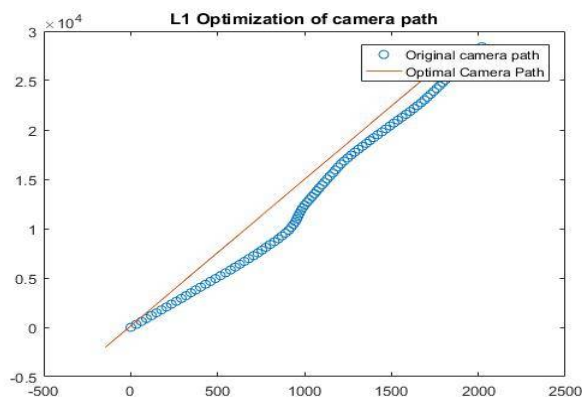


fig.8. optimal camera path using L1 optimization method



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L1 term in objective function consist of the first, second and third derivatives of optimal path. But unlike Grundmann’s equation we retain Ct in optimization. The introduction of L2 norm can automatically set weights of three kinds of segments according to shape of original camera path.

V. MATHEMATICAL EVALUATION

While performing video stabilization algorithm sometimes it may not be possible that we get stabilized video visually for getting perfect result we need to perform mathematical evaluation of video for stability of video. For that in this paper we used PSNR (Peak signal- to –noise ratio) value. PSNR is simple metric of image quality. They can be extended to video quality assessment by comparing still images on frame-by-frame basis.

$$PSNR = 10 \log_{10} \left(\frac{MAX_1^2}{MSE} \right)$$

$$= 20 \log_{10} \left(\frac{MAX_1}{\sqrt{MSE}} \right)$$

Here MAX_1 – maximum possible value of image
 MSE- mean square error

VI. EXPERIMENTS

To evaluate the performance of the proposed algorithm, we applied our algorithm on multiple videos. We also compare two methods for better understanding and for better results. In video stabilization method for performance assessment we not only giving visual results but also mathematical result is also obtained.

For mathematical result we obtained PSNR value of original video , L1 optimization video stabilization method value, Mixed L1-L2 optimization values are compared. After comparing mathematical results we got best value for Mixed L1-L2 optimization method.

Table1: mathematical comparison of PSNR value for different video

Type of video	PSNR value of Original video	PSNR value of L1 optimization	PSNR value of Mixed L1-L2 Optimization
Standing camera	20.9988	36.3953	36.8396
Walking camera	23.2265	36.1292	37.4170
Car mounted camera	17.3050	31.9539	32.5958

VII. CONCLUSION

We have implemented two method for video stabilization first is L1 Optimization and second is Mixed L1-L2 Optimization, by using both methods we obtain stabilized video. In mixed L1-L2 optimization method we obtain more stabilized video as well as preserve as much as information more possible than the L1 optimization method. We also find PSNR ratio for original video and L1 and mixed L1-L2 Optimization and compered them for better understanding.



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