Towards High-Quality Parallel Stabilization

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Abstract: With the widespread use of handheld devices and unmanned aerial vehicles (UAVs) that has the ability to record video sequences. Digital video stabilization becomes more important as these sequences are usually shaky undermining the visual quality of the video. Digital video stabilization has been studied for decades yielding an extensive amount of literature in the field. However, most of them are highly sequential. In this paper, we present a new parallel technique that exploits the parallel architecture found in modern day devices. The algorithm divides the frame into blocks and estimates a camera path for each block to better enhance the estimation of the transformation needed to adjust for the shakiness of the video.

1 INTRODUCTION

The introduction of digital cameras in cell phones and the spread of unmanned aerial vehicles (UAVs) made the capture of video sequences much easier. However, these sequences usually suffer from undesired high frequency jittering due to the movement of the camera holder or the movement of the UAV platform. This jittering result in video sequences with poor visual quality, plus it undermines the use of other algorithms used for object detection and tracking which are vital in many video applications (e.g., surveillance systems, search and rescue .. etc.). The aim of digital video stabilization is to remove the unwanted jittering producing sequences with better quality.

Digital video stabilization has been studied for years in the field of computer vision. Generally, Stabilization algorithms perform three main operations: 1) Estimating the camera motion (shaky path), 2) Estimate new smooth camera path, 3) Refine the original shaky path using the smoothed one. Digital video stabilization approaches fall broadly into two categories based on the motion estimation model: 1) 2D Stabilization, 2) 3D Stabilization. The 2D methods (Matsushita et al., 2006; Grundmann et al., 2011) estimate a linear transformation either affine or homography between successive frames. And the camera path is formed by the concatenation of the linear transformations. In general these methods are robust and fast. However, they suffer a limitation as they cannot deal with the parallax caused by depth information in the scene. 3D methods (Liu et al., 2012; Liu et al., 2009)on the opposite hand can handle the parallax induced by the depth information and produce highly stable sequences. However, their motion estimation model is complex and less robust than the 2D methods. Recent approaches tried to combine both benefits of the 2D and 3D as shown in (Goldstein and Fattal, 2012) by employing the concepts of epipolar geometry. However, these methods require tracking features for long period of time which can be difficult in sequences with rapid motion or occlusion.

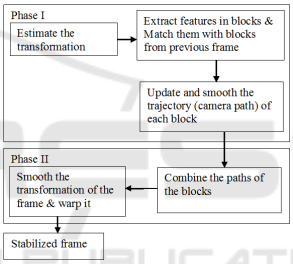

Figure 1: Block diagram of the proposed algorithm.

This paper falls in the first category aiming to provide robust and high quality stable sequences from 2D linear transformations. This paper contribution is in two folds. 1) We propose a novel algorithm in the estimation of the frame trajectory. Specifically, the proposed algorithm divides the image into blocks and maintains the trajectory for each block so that each block has its own camera path, then for any given frame the paths of its blocks are combined to give a better estimation for its transformation. Figure 1 summarizes the proposed algorithm. 2) Unlike, most of the algorithms in the literature, the proposed al-

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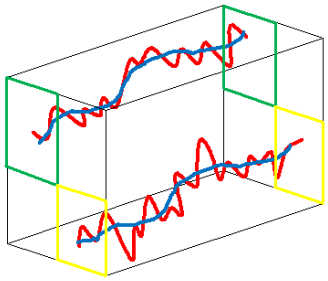
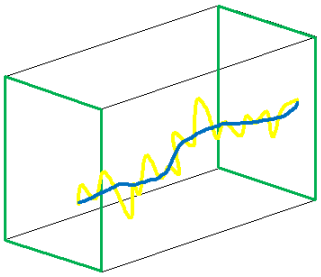


(a) Original block shaky path in red, smoothed path for the block in blue.



(b) Original frame path in yellow, smoothed path for the frame in blue.

Figure 2: Camera paths.

gorithm is highly parallelizable exploiting the parallel architecture found in modern computers and handheld devices ensuring real time performance. The remainder of this paper is organized as follows: related work is presented in section 2; a detailed description of the proposed algorithm is presented in Section 3, followed by the evaluation criteria and results in Section 4. A discussion of the results is presented in section 5. Finally, Section 6 concludes the paper and directs future work.

2 RELATED WORK

Stabilization methods can be categorized into two main categories: 1) 2D Methods, 2) 3D methods. The 2D methods estimates linear transformations (affine or homography) between successive frames and smooth the trajectory over time to produce a stabilized video. Wang et al.(Wang et al., 2011) assumes the motion model fit a polynomial curve e.g. a cubic curve to smooth the parameters. Irani et al. (Irani et al., 1994) deals with complex video sequences and attempts to estimate a homography transformation which stabilizes a dominant planar region in the video. Matsushita et al.(Matsushita et al., 2006) extends the stabilized frames to become full frames and apply low pass filter for smoothing the parameters over time. Grundmann et al. (Grundmann et al., 2011) proposes the application of L1- norm optimization model to smooth the camera path to follow cinematography rules. This technique was integrated into Googles YouTube. 3D methods require the recovery of structure from the video sequence including 3D camera poses and depth structures. These structures can computed using Structure from motion (SFM) techniques (Agarwal et al., 2011; Furukawa et al., 2010; Jiang et al., 2012; Wu, 2013). Buehler et al.(Buehler et al., 2001) computes SFM in a general un-calibrated camera setting and solved using the bundle adjustment method (Triggs et al., 2000). Liu et al. (Liu et al., 2009) proposes a full 3D stabilization method by introducing content-preserving warps for the novel view synthesis. Liu et al. (Liu et al., 2012) uses a depth camera to recover depth information and perform 3D video stabilization. Since 3D reconstruction of a full video is still challenging. Goldstein and Fattal (Goldstein and Fattal, 2012) uses the concepts of epipolar geometry to avoid 3D reconstruction. Wang et al.(Wang et al., 2013) proposes a new representation of each feature trajectory as a Bezier curve and then smoothed over time. Liu et al. (Liu et al., 2011) choose to smooth basis trajectories of the subspace (Irani, 2002) which are extracted from long feature tracks of 50 frames or more. This method achieves high quality stabilization that is similar to the full 3D methods, while avoiding the need of a full 3D reconstruction and using long feature trajectories instead. This technique has been integrated in Adobe After Effects as a video stabilization function named Warp Stabilizer. Recently, Liu et al.(Liu et al., 2013) proposes an extension of the method to cope with stereoscopic videos. However, the need of long feature trajectories is difficult to achieve especially in videos with quickly changing scenes or a lot of occlusions. Regardless if the algorithms are 2D or 3D, almost all of them are either highly sequential or offline stabilizers. Previous work on real-time stabilization as in Wang et al. work (Wang et al., 2011) the motion model was restricted to translation only. Litvin et al.(Litvin et al., 2003) the algorithm used Kalman filtering to extend the model to be a full 2D affine model with translation and rotation. However, these techniques sacrifice much of the robustness and visual quality to achieve real time performance. The proposed method aims at providing parallel, real time performance without sacrificing loss in the robustness or the visual quality provided by the offline stabilizers. By dividing the frame into blocks and smoothing their trajectory over time allowing better estimation for the frame transformation that can adopt with various videos.

3 PROPOSED ALGORITHM

The proposed method uses a novel technique to estimate the transformation parameters for a video frame and smooth the parameters over time in two phases, as illustrated in Figure 1. The algorithm description is discussed in the next sections.

3.1 Algorithm Description

Phase I: At each frame, the frame is divided into N blocks with window overlap of 60% that has been defined empirically through experiments on various videos some of which are shown in Figure 4. The overlap ensures that the features are well tracked along the boundaries. Then, for each block features are extracted using good features to track(Shi and Tomasi, 1994). These features are then tracked in the same block in the next frame using optical flow method. An affine transformation denoted by H is then estimated for each block. The camera path of the block is then smoothed over time using a Gaussian low pass filter with sigma σ_0 producing a more stable camera path for that block. So let P_t denotes the original shaky block path, which is formed by the concatenation of the blocks affine transformations over time as defined by equation 1. The desired (smoothed) camera path for the block C_t is calculated based on equation 2.

$$P_t = \prod_{i=0}^{i} H_i. \quad (1)$$

$$C_t = P_t * G_t \quad (2)$$

where G_t is the Gaussian low pass filter function with sigma σ_0. Phase II: With each block camera path smoothed individually from phase I. these paths are then combined to form an estimate for the transformation parameters for their corresponding frame. The paths are combined using another low pass 2D Gaussian with sigma σ_1 which gives more weight to the central blocks of the frame as the central blocks of the frame should contain the dominant motion in the frame. Let $C_{t,i}$ represent the smoothed block path the frame estimation $\acute{P}_t$ is derived by equation 3.

$$\acute{P}_t = C_t * W(X,Y) \quad (3)$$

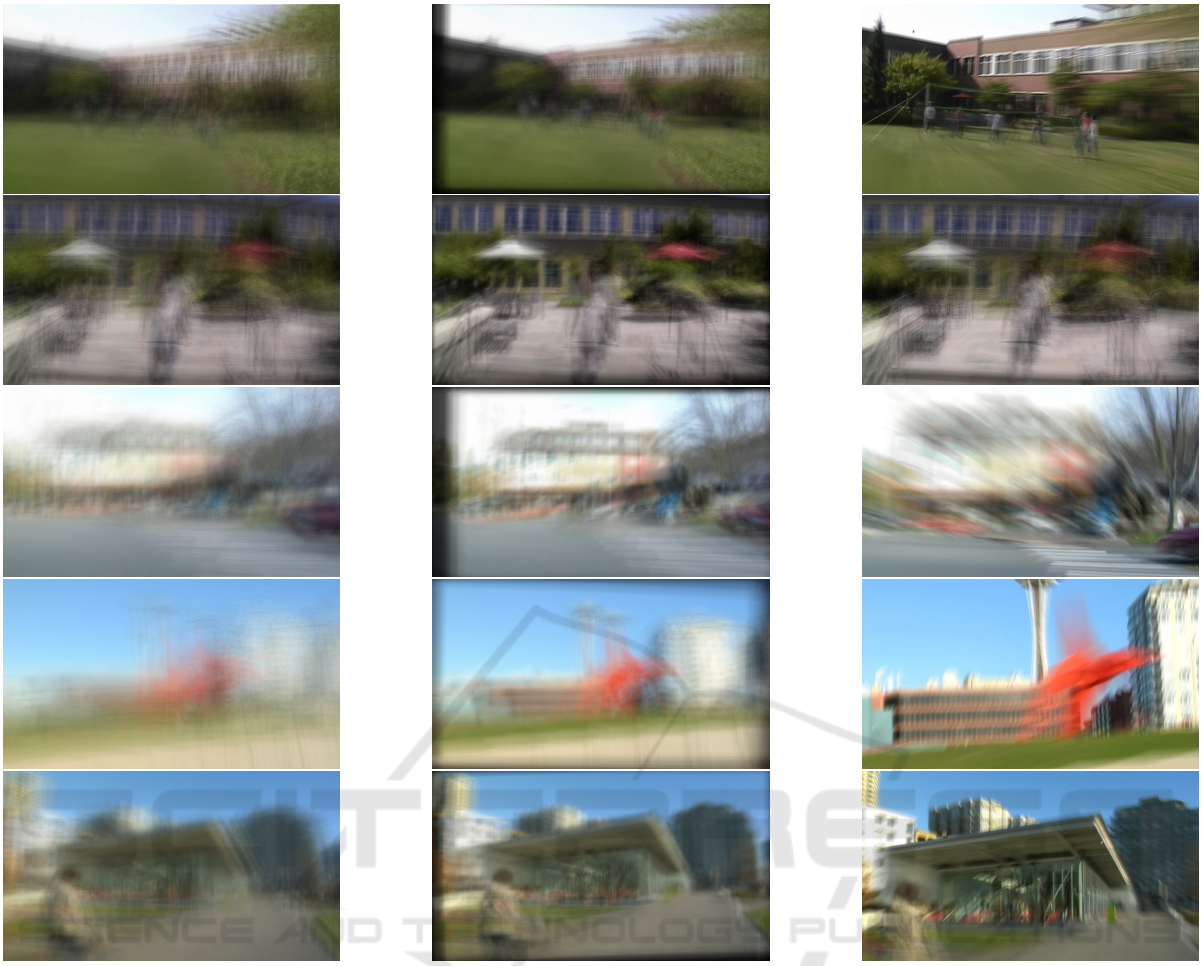
where $W(X,Y)$ is the 2D Gaussian window function with sigma σ_1. Then as a final step the final camera path for that frame is smoothed within a window of neighbouring frames using a third low pass Gaussian filter with sigma σ_2 to produce the final transformation parameters for the frame in a similar procedure to the smoothing of the block path defined by equation 2. As seen the algorithm is highly parallelizable as the estimation of the block transformation does not need any communication or dependency between data needed by different processors to produce results so the process can be easily parallelized.

Algorithm 1: The Proposed Algorithm.

1: **Input:** Input Frame.
2: Divide the frame into blocks(Input frame).
3: **for** each block $i \in N$ Parallel **do**
4: Extract good features to track.
5: Track the features into previous block.
6: Evaluate good matches.
7: Estimate affine transformation.
8: In case no good transformation can be calculated, the estimation is replaced by the transformation of the same block from previous frame.
9: For each block in the neighborhood window, the trajectory is smoothed using a low pass Gaussian filter.
10: A new transformation is estimated based on the smoothed trajectory.
11: **end for**
12: For each block in the frame, their estimation is smoothed using a 2D Gaussian kernel to estimate the transformation for the frame.
13: The trajectory of the frame is then smoothed based on the Gaussian filter with the neighboring frame in the window.
14: The final transformation is then estimated based on the smoothed trajectory of the whole frame.
15: The final stabilized frame is computed through warping the input frame.
16: **Output:** Stabilized Frame.

3.2 Implementation

In the implementation of the proposed algorithm, the number of blocks N =16 for videos with frame height of 720 and width of 1280. The size of the neighborhood used for smoothing was set to 30 in both cases of smoothing on block and frame level. The sigma of the Gaussian filter used in block smoothing is small σ_0 =0.3 and σ_1 = 0.5. Only σ_2 is set to larger value to suppress any fluctuations and enforce more smoothness on the path of the camera, so σ_2 is set to 10. All the values were set empirically based on experimenting with different video sequences. Then Using OpenMp directives the estimation of the transformation for each block is done in parallel. The rest of the implementation for feature extraction, matching and estimation of transformation and warping of the frames is based on OpenCV implementation. Algorithm 1 shows a pseudo-code of the implementation.



(a) Original Mean of Sequence (b) Our Stabilized Sequence Mean (c) Google's Youtube Stabilized Sequence Mean

Figure 3: Sequence Mean Comparison.

4 RESULTS

The proposed algorithm has been tested on both the datasets provided by (of Central Florida,) (Grundmann et al., 2011) and (Liu et al., 2009). The evaluation criteria are based on (Morimoto and Chellappa, 1998) measuring the average fidelity with equation 4, the mean of the sequence to assess the visual quality improvement and also the path of the camera.

$$PSNR_{dB}(I_1, I_0) = 10 \log \frac{(255)^2}{MSE(I_1, I_0)} \qquad (4)$$

where MSE is the mean squared error measuring the error per pixel from the optimal stabilized result, and the 255 represents the maximum intensity a pixel may have. Figure 3 shows a comparison of the mean of the stabilized sequence from the results from Googles YouTube stabilizer at the right and the result from our proposed algorithm at the middle. by examining the images, it can be seen that our proposed method can produce results that are comparable to one the state of the art stabilization algorithms. However, in sequences with high jitter as in the fourth sequence, our algorithm performs poorly which will be discussed later in the upcoming section. In Table 1 the value of the fidelity after the stabilization is significantly higher. In Figures 4-6 the trajectory of the sequence in Y-axis, X-axis and the rotation angle respectively plotted with the original trajectory in blue and the smoothed version in green, it can be clearly seen that the smoothed trajectory does not suffer the high fluctuations found on the original trajectory.

Table 1: Comparison between the fidelity of the original sequence (left) ,using our method (middle) and Stabilized Fidelity from Google's Youtube(right).

Sequence	Original Fidelity	Our Stabilized Fidelity	Google's Youtube
Seq. 1	40 dB	56 dB	53 dB
Seq. 2	45 dB	50 dB	66 dB
Seq. 3	42 dB	60 dB	59 dB
Seq. 4	42 dB	53 dB	77 dB
Seq. 5	34 dB	45 dB	50 dB

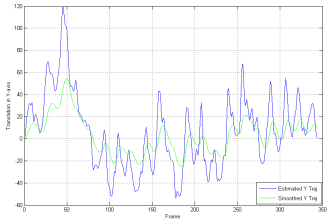


Figure 4: Comparison between the original trajectory (blue) and the smoothed trajectory (green) for Y-direction.

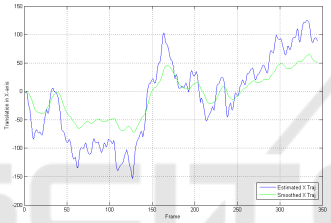


Figure 5: Comparison between the original trajectory (blue) and the smoothed trajectory (green) for X-direction.

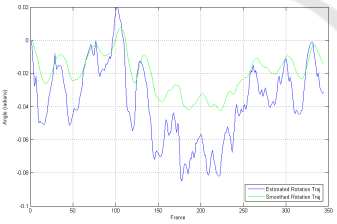


Figure 6: Comparison between the original trajectory (blue) and the smoothed trajectory (green) for the angle of rotation.

5 DISCUSSION AND PERFORMANCE ANALYSIS

5.1 Discussion

The proposed algorithm does perform well on short sequences, However as seen in Figure 3 the mean sequence still suffers some jittering especially in sequence with extreme jittering as maintaining the camera path for each block will tend to make some drifts in the estimations this can be seen also in Figure 5. as the smoothing of the X-direction drifting away from the estimation and instability in both the estimation and the smoothing increases over time. To overcome this drawback more constraints will be added to the system to ensure the calculations in both the block and frame level. Generally, we find that the 3D reconstruction method gives the best results when successful. However, the proposed method produces videos with high visual quality and takes benefit of the robustness and simplicity of 2D methods and not restricted to one type of transformation.

5.2 Runtime Analysis

The proposed algorithm has been tested on the following configurations: Intel Quad Core processor @2.20 GHz. The average running time for the whole algorithm is around 20 fps, taking around more than half the time needed to process one frame in Phase I. Typically the running time for this phase increases with increasing the number of blocks in the frame and with extending the size of the window used for smoothing.

6 CONCLUSION AND FUTURE WORK

This paper presented a parallel technique in stabilization based on 2D linear transformations with running time suitable for real time systems and with high visual quality compared to offline and 3D stabilizers. In the future, the algorithm will be tested in more datasets, plus extending the work to handle featureless scenes and longer sequences. Also, the addition of new constraints on the smoothing function to allow the process of longer sequences to produce the highest stabilization quality.

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