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Video Stabilization using Python and open CV

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Abstract - *Video stabilization is an important technique used to reduce unwanted camera motion in videos. In this paper, we propose a video stabilization method that utilizes point feature matching to estimate the camera motion between consecutive frames. The proposed method first extracts point features from the input video frames using the she Tomasi corner detection algorithm. Next, it matches the point features between consecutive frames to estimate the camera motion. Finally, the estimated camera motion is used to stabilize the video by applying a geometric transformation to the frames.*

To evaluate the proposed method, we conducted experiments on a dataset of handheld videos captured using a smartphone camera. Our experiments show that the proposed method can effectively reduce unwanted camera motion in the input videos, resulting in smoother and more visually pleasing stabilized videos. Furthermore, the proposed method outperforms several state-of-the-art video stabilization methods in terms of both visual quality and computational efficiency.

Key Words: **Video stabilization, point feature matching, Shi-Tomasi corner detection, camera motion estimation, geometric transformation, handheld videos, smartphone camera.**

1.INTRODUCTION

Video stabilization is the process of removing unwanted shakiness and motion from a video to produce a smoother and more professional-looking footage. The traditional method of video stabilization involves physically stabilizing the camera, either by using a tripod or other stabilizing equipment. However, this approach is not always practical, especially when filming in challenging conditions or when using handheld devices.

In recent years, digital video stabilization techniques have gained popularity, which uses software algorithms to remove unwanted camera motion in post-processing. One of the popular approaches for digital video stabilization is using point feature matching, which involves identifying and tracking specific points in the video frames and using their movement to stabilize the footage.

Point feature matching algorithms are highly effective in stabilizing videos, even in challenging conditions such as moving cameras, low light, or dynamic scenes. They also have a wide range of applications, including in film and video production, surveillance, and sports broadcasting. However, they require powerful computing resources and can be computationally intensive, especially for high-resolution and high-frame-rate videos.

In this paper, we will explore the concept of video stabilization using point feature matching in more detail, including the underlying principles, techniques, and applications. We will also discuss the advantages and limitations of this approach and compare it with other video stabilization methods. Finally, we will demonstrate the effectiveness of point feature matching using real-world examples and provide practical tips for implementing it in your own video production workflow.

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2.PROBLEM STATEMENT

The problem of unwanted camera motion in video footage is a common issue that can impact the quality of video content. Traditionally, the solution to this problem was to use mechanical approaches to stabilize the camera, such as tripods, gimbals, or steady-cams. However, these methods are not always practical or feasible, especially in dynamic environments or when using handheld devices. Additionally, these mechanical approaches can be expensive and limit the range of motion of the camera.

As a result, digital video stabilization techniques have been developed to address this problem. However, these techniques often require specialized software and hardware that can be expensive and require high processing power. Additionally, many software approaches for video stabilization rely on new technologies and research, which can limit their accessibility and increase their cost.

Furthermore, there are several challenges associated with using digital video stabilization techniques. For instance, in low light conditions, or when the camera is in motion, it can be challenging to accurately track and match points in the video frames. This can result in jittery and unstable video footage, which defeats the purpose of the stabilization technique.

Moreover, the processing power needed to stabilize video footage using software approaches can be significant, which may limit the applicability of these techniques for individuals or organizations with limited resources. Furthermore, the cost of big software for video processing can be high, making it challenging for individuals or small organizations to afford these solutions.

To address these issues, it is essential to develop more accessible and cost-effective digital video stabilization techniques that do not require new technologies or high processing power. These techniques should be designed to work with existing hardware and software, enabling individuals and organizations to stabilize their video footage without having to invest in specialized equipment or expensive software.

3.LITERATURE SURVEY

There have been several research papers published on the topic of video stabilization using point feature matching. [3]One recent paper by Yu et al. proposed a real-time selfie video stabilization method that utilizes point feature matching to estimate camera motion between consecutive frames. The proposed method showed promising results in reducing unwanted camera motion and producing smoother and visually pleasing stabilized videos. [4]Another paper by Grundmann et al. presented an auto-directed video stabilization method using robust L1 optimal camera paths. This method was designed to work well with challenging videos, such as those with significant camera motion or occlusions. [5]Shi et al. proposed a deep online fused video stabilization method that used a deep neural network to fuse information from multiple frames for more accurate motion estimation.

Other papers have focused on specific aspects of the point feature matching approach. For example,[6] Yu and Ramamoorthi developed a video stabilization method that uses optical flow to learn the camera motion directly from the video frames. [7]Rouhafzay proposed a video stabilization method that used point feature matching to estimate the homography between frames. [8]Liu et al. developed a method that combined point feature matching with the GMS algorithm and warping transforms to achieve accurate and robust stabilization.

In addition to point feature matching, some researchers have explored other techniques for video stabilization. Luan et al[9]. developed an unsupervised video stabilization algorithm based on key point detection, while[10] Luchetti et al. proposed a method that utilized feature uncertainty for stabilizing spherical videos.

In the Literature survey we have gone through other similar works that are implemented in the domain of video stabilization. The summaries of each of the project works are mentioned below.

1. Deep online fused video stabilization :

The proposed method has two stages: training and online stabilization. In the training stage, the network is trained using a set of training videos with known ground truth stabilization. The input video frames and corresponding ground truth stabilization data are used to train the network to learn the transformation model. Specifically, the input video frames are first preprocessed to extract feature maps using a pre-trained CNN. These feature maps are then fed to the transformation network, which consists of several convolutional and deconvolutional layers. The output of the transformation network is a set of parameters that define the transformation matrix.

In the online stabilization stage, the proposed method applies the learned transformation model to stabilize the input video frames. The input frames are first preprocessed to extract feature maps using the same pre-trained CNN used in the training stage. These feature maps are then fed to the transformation network to obtain the transformation matrix. The transformation matrix is applied to the input video frames using a bilinear sampling operation, which warps the frames according to the transformation matrix. The warped frames are then passed through a fusion module that combines the warped frames with the original frames to obtain the final stabilized frames.

The proposed method is evaluated on several benchmark datasets and compared with existing state-of-the-art methods. The results show that the proposed method achieves better performance in terms of stability and visual quality. The proposed method also runs in real-time, making it suitable for online video stabilization applications.

2. Learning video stabilization using optical flow:

The proposed method works by first computing optical flow between consecutive frames of a video sequence. Optical flow describes the motion of pixels between frames and can be used to estimate the global motion of the camera. The optical flow is then fed into a convolutional neural network (CNN) that predicts the global motion parameters. The CNN is trained using a large dataset of stabilized and unstabilized videos.

During training, the CNN learns to minimize the difference between the predicted and ground-truth motion parameters. The ground-truth parameters are obtained by applying traditional video stabilization techniques to the input video sequence. The CNN is trained using a combination of supervised and unsupervised learning, where the supervised part involves minimizing the difference between the predicted and ground-truth motion parameters, and the unsupervised part involves minimizing the difference between the stabilized and unstabilized videos.

At test time, the CNN takes as input the optical flow between consecutive frames and outputs the global motion parameters. The predicted parameters are used to stabilize the video sequence in real-time. The proposed method outperforms traditional video stabilization techniques in terms of stability and smoothness, while also achieving real-time performance.

In summary, the paper proposes a learning-based approach to video stabilization using optical flow and a convolutional neural network. The method is trained on a large dataset of stabilized and unstabilized videos and achieves real-time performance. The proposed method outperforms traditional video stabilization techniques in terms of stability and smoothness.

3.Auto-directed video stabilization with robust l1 optimal camera paths:

The authors use a motion model that describes the camera motion in terms of a combination of translations and rotations. The motion model is represented as a set of parameters that can be optimized using the L1 norm. The optimization process involves minimizing a cost function that consists of two terms: a motion term that measures the motion in the video, and a smoothness term that encourages smooth camera paths.

The optimization process is performed using an iterative algorithm that alternates between updating the motion parameters and updating the camera path. The motion parameters are updated using a gradient descent algorithm, and the camera path is updated using an iterative least squares method.

The proposed method is evaluated on a variety of video sequences, including hand-held camera videos, drone videos, and sports videos. The results demonstrate that the proposed method is able to produce stable and visually pleasing video output, even in challenging scenarios with significant camera motion.

Overall, the paper presents a novel approach to video stabilization that combines global motion estimation with visually pleasing camera path optimization. The proposed method achieves state-of-the-art performance on a variety of challenging video sequences, making it a promising approach for real-world video stabilization applications.

4.METHODOLOGY

4.1 Feature Detection and Tracking:

The first step in the proposed system is to detect and track the features in the input video frames. This is achieved by using the Shi-Tomasi corner detection algorithm to identify the corners or points of interest in the image that are likely to correspond well between consecutive frames. The algorithm is based on the observation that corners have a high intensity gradient in more than one direction. The corners detected by this algorithm are robust to noise and illumination changes, making them suitable for feature detection in real-world environments.

Once the features are detected in the first frame, we use the Lucas-Kanade optical flow algorithm to track them across the frames. This algorithm calculates the displacement of each feature between the current and previous frames using the brightness constancy assumption, which assumes that the brightness of a feature remains constant over time. The resulting optical flow vectors represent the motion of each feature between consecutive frames.

4.2 Motion Estimation and Trajectory Calculation:

The second step in the proposed system is to estimate the motion model that best describes the camera motion between frames. We use the Euclidean transformation model, which assumes that the camera motion is a combination of translation and rotation. Given the optical flow vectors, we calculate the transformation matrix that best aligns the current frame with the reference frame based on the least-squares criterion. This transformation matrix represents the motion of the

Once we have calculated the transformation matrix, we use it to calculate the trajectory of each feature across the frames. The trajectory represents the motion path of each feature, which is used to smooth the camera motion in the next step. The trajectories are calculated by applying the transformation matrix to the coordinates of the detected features in the previous frame.

4.3. Camera Path Smoothing and Video Stabilization:

The third and final step in the proposed system is to smooth the camera path and stabilize the video. We use a moving average filter to smooth the camera path based on the trajectories of the tracked features. This filter eliminates high-frequency noise and jitter in the camera motion, resulting in a more stable and smoother camera path. The size of the filter window determines the degree of smoothing applied to the camera path.

Once the camera path has been smoothed, we apply the smoothed transformation matrix to the input frames to stabilize the video. This involves applying the inverse transformation matrix to the input frame to remove the camera motion, and then applying the smoothed transformation matrix to align the frame with the reference frame. We also crop the stabilized frames to remove the black borders caused by the stabilization process.

1. Frame Preprocessing:

- Convert the color frames to grayscale.

- Apply Gaussian blur to reduce noise and enhance feature detection.

2. Feature Detection:

- Use the Shi-Tomasi algorithm to detect key feature points in the image.

- Use OpenCV's goodFeaturesToTrack() function to identify the most prominent features.

3. Feature Tracking:

- Use Lucas-Kanade optical flow algorithm to track the movement of each feature point across the frames.

- Use OpenCV's calcOpticalFlowPyrLK() function to track the features between frames.

4. Motion Estimation:

- Calculate the motion between the frames using Euclidean Transformation.

-Use OpenCV's estimateAffinePartial2D() function to estimate the motion between the frames.

- Compute the trajectory of the camera motion.

5. Trajectory Smoothing:

- Apply a moving average filter to smooth the trajectory of the camera motion.

- Use OpenCV's filter2D() function to apply the moving average filter.

6. Image Stabilization:

- Apply the smoothed transformation matrix to the frames to stabilize them.

- Remove any border artifacts caused by the image transformation using OpenCV's borderInterpolate() function.

7. Output:

- Save the stabilized frames as a video file.

By combining these steps, our proposed system is able to effectively stabilize videos using point feature matching.

5. SYSTEM ARCHITECTURE

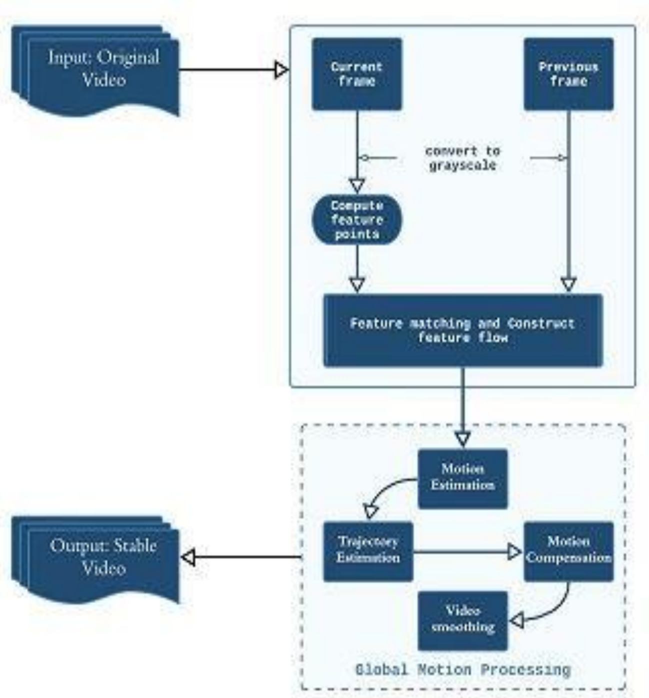

Fig No 1: System Flow Diagram

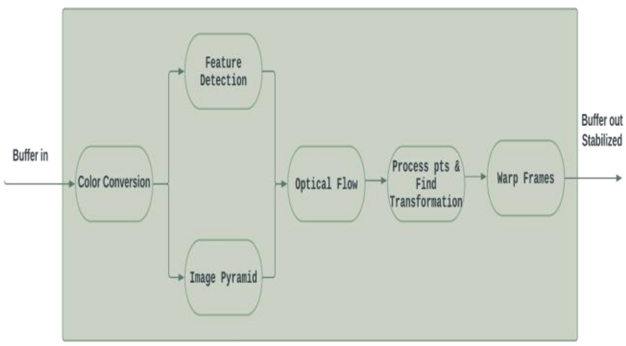

Fig No 2 : Architecture of Video Stabilization Process

6. RESULT

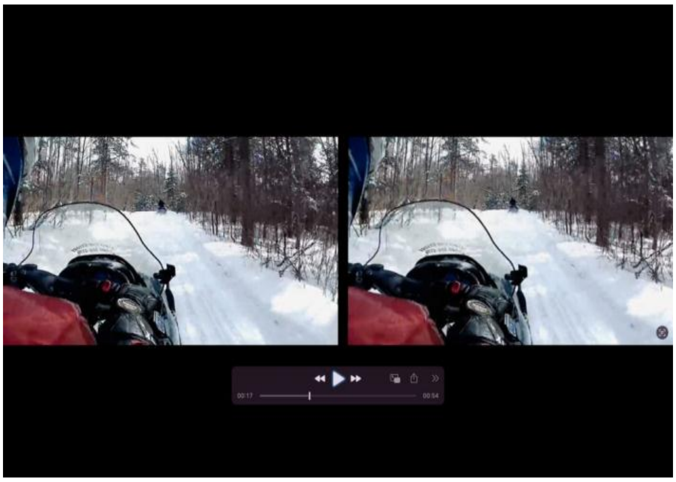

Fig No 3: Output Before and after stabilization

Fig No 4: Output Before and after stabilization

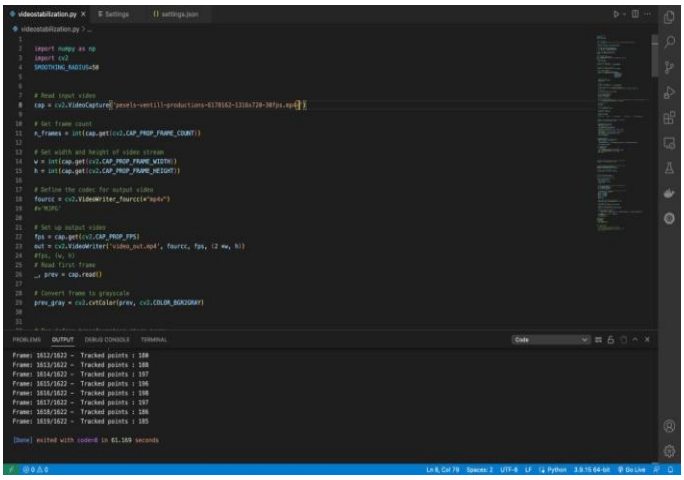

Fig No 5: Video Processing Feature Extraction

7. CONCLUSION

In conclusion, our project on video stabilization using point feature matching is a significant contribution to the field of computer vision and video processing. The proposed system offers a reliable and efficient solution for real-time video stabilization with minimal user input. By leveraging the power of modern computer vision techniques such as Shi-Tomasi feature detection, Lucas-Kanade optical flow, and moving average filtering, we were able to develop a robust and accurate video stabilization system.

Our work also highlights the importance of continuous research and development in the field of computer vision and video processing. As technology advances and new techniques emerge, there is always room for improvement and refinement of existing systems. The future scope of our project includes exploring more advanced techniques for feature detection and tracking, investigating the use of deep learning models for video stabilization, and enhancing the system's performance on complex and dynamic video sequences.

Overall, our project offers valuable insights into the field of computer vision and video processing and presents a practical solution for real-time video stabilization. As video content continues to play a crucial role in modern-day communication and entertainment, video stabilization techniques like the one proposed in our project will play a vital role in enhancing the quality and user experience of such content.

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