ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 7, Issue 12, December 2019

Video Stitching Based on Different Feature Extraction Techniques

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ABSTRACT: Stitching collection of images from a variety of viewpoints into a panoramic image is a common function. But when extending this panoramic image to video, there are many challenges. Video stitching has to deal with moving objects in the overlapped area which often cause problems of structural misalignment or ghost effect. The goal of multi-view video stitching is to generate a panoramic video from multiple overlapping video streams captured by relatively displaced cameras. The input to a multi-view video stitching program is multiple, overlapping videos captured from different camera views which are together called a multi-view video, and the output is a panoramic video of wider field of view constructed by merging and stitching the individual videos of the input multi-view video. Feature extraction, Feature Matching, homography estimation, Stitching and stabilization are the different steps needed to generate panorama video. Panoramic video stitching is one of the common research area in computer vision, image/video processing and computer graphics and has many wide applications.

KEYWORDS: feature extraction, feature matching, homography estimation, video Stitching, blending

I. INTRODUCTION

Multi-view image stitching, also called image mosaicing or panorama stitching, is a basic and long-studied problem of computer vision, with applications in robotics, architecture, industrial inspection, surveillance, computer graphics, and mobile devices.The goal of multi-view image stitching is to generate a panoramic image from multiple overlapping images of the same scene, captured at displaced locations. Although multi-view image stitching has been a focus of interest in the computer vision community, much less attention has been paid to the closely related topic of multi-view video stitching.

The goal of multi-view video stitching is to generate a panoramic video from multiple overlapping video streams captured by relatively displaced cameras. When capturing a multi-view video, the cameras can be fixed or moving while they are capturing the videos, but their relative geometry is unchanged during the capture procedure. The input to a multi-view video stitching program is multiple, overlapping videos captured from different camera views which are together called a multi-view video, the output is a panoramic video of wider field of view constructed by merging and stitching the individual videos of the input multi-view video.

The unfixed optical centers of cameras and objects moving across cameras are the challenges to video stitching. Besides, parallax problem exists when objects are close to cameras. Therefore, video stitching is a challenging task. Another challenge is that projective transformation usually produces shape distortion in non-overlapping regions, which cause wrong depth perception to the viewer. The other difficulty is that exposures for images captured by different cameras may be inconsistent due to different light directions, thus making the video stitching more challenging. One challenge in video stitching under this circumstance is that videos captured by moving cameras often appear shaky. Applying image stitching methods to shaky videos may have drawbacks.

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Vol. 7, Issue 12, December 2019

Due to shakiness in the captured images there may be strong perspective distortions. There will not be temporal smoothness by stitching in the frame-by-frame fashion so that jitters would become visible.

II. RELATED WORK

In **[1]** Tan Su, YongweiNie, Zhensong Zhang, Hanqiu Sun, and Guiqing Li proposed a hand-taken video stitching method which combines the techniques of video stitching and stabilization together into a unified optimization framework. In this way, the method computes the most optimal stitching results.It consists of two stabilization terms and one stitching term for achieving unified camera paths optimization formulation.WeiXu**[2]**, proposed a continuity aware Kalman filtering scheme for rotation angles for video stabilization and jitter removal.This method produces long, high-resolution panoramic videos and also proposed constrained and multigridSIFT matching schemes. These methods can reduce the computational time and memory requirement for panoramic video stitching. In **[3]**ShishirMaheshwari proposed method employs the Harris corner detection algorithm for corner detection. The features are detected and the feature descriptors are formed around the corners. The feature descriptors from one image are matched with other image for the best closeness and only those features are kept, rest are discarded. From the features transformation model is estimated and the image is warped correspondingly. After the image is warped on a common mosaic plane, remove the intensity seam using Graph cut method with minimum cut/ maximum flow algorithm. In **[5]** image stitching techniques can be categorized into two general approaches such as direct and feature based techniques. Feature based technique is used to determine a relationship between the images through different features descriptors from the processed images. Feature extraction, feature Matching, outlier Elimination, stitching and blending are the steps used to generate the panorama. Different feature extractors such as SIFT(scale invariant feature transform), SURF(speeded up robust features), ASIFT(affine scale invariant feature transform) and ASURF(affine speeded up robust features) are used to create panorama. Rather than feature based technique to create panorama, correlation can also be used . Panoramic images created by using different methods are evaluated based on the quality of the output mosaic and the time needed to generate the panorama.Tomoyuki Shimizu et.al **[11]** proposed a fast video stitching method based on global motion tracking for motion-compensated frames, which can construct high definition or panorama video from standard definition video streams. Our method consists of two stages. The first stage calculates projection matrix between stitched frames of each input video stream. Since the result of the first stage may have some matching error, the errors can be removed by doing some fine adjustment in the second stage. In**[8]**Shuo-Han and Shang-Hong Lai proposed a real time video stitching which can stitch videos acquired from multiple moving cameras. The proposed algorithm estimates homography in both spatial and temporal domains. In spatial domain RANSAC is used while in temporal domain linear interpolation is done. Linear blending in the overlapping region used to generate panoramic view with cylindrical warping.

III.MAIN COMPONENTS OF VIDEO STITCHING

The overall structure of the proposed method is shown in figure 1.Calibration, Registration and Blending are the steps needed togenerate panoramic video.

A. Calibration

To minimize differences between an ideal lens and the camera-lens model, calibration was used. These differences are resulted from optical defects such as distortions and exposure differences between videos.In order to reconstruct the 3D structure of a scene from the pixel coordinates, intrinsic and extrinsic camera parameters are recovered. To define the location and orientation of the camera reference frame with respect to a known world reference frame, extrinsic camera parameter is used. To link the pixel coordinates of an image point with the corresponding coordinates in the camera reference frame, intrinsic camera parameters is used.

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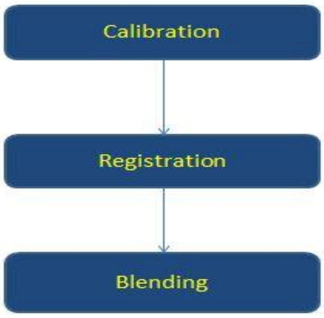

Figure1: The main components of video stitching

B. Registration

Registration is the core of a mosaicing procedure. Videos are converted into frames of equal size. Its purpose is to create geometric correspondence between frames. Therefore, we can compare frames and apply other steps appropriately. Frame registration is defined as the process of aligning two or more frames. Image blending is processed to make the transition from one frame to another frame smoother. So, the joint between two frames can be removed.

C. Blending

Blending is applied to the stitched image so to make seamless. There are mainly two ways for blending. One is called alpha feathering blending and another one is Gaussian pyramid. Alpha blending takes weighted average of two images. Gaussian pyramid merges the images at different frequency bands and filters them accordingly. The lower the frequency band, the more it blurs the boundary.By preserving the pixels away from the boundary,Gaussian pyramid blurs the boundary.

IV. VIDEO STITCHING APPROACHES

Another approaches are the direct and feature based techniques. By minimizing pixel to pixel dissimilarities,direct techniques can be employed.By extracting a sparse set of features and then matching these to each other,the feature based technique works. Video stitching methods is also classified into those based on static cameras and moving cameras according to the video acquisition manner.

A. Static Cameras

Classical video stitching system focuses on stitching images captured by static cameras andan object detection method is performed**[3]**. The selected frames of the input videos are firststitched to generate a stitching template, in which there is no object moving across the overlapping regions between the input videos. The subsequence frames are in torn stitchedaccording to the template, and then the template is updated when there are moving objects. Rav-Acha et al. embedded the detected dynamic contents into the stitched images with a stitching algorithm and an object detection. Much consistent information iscontained in the frames of spatially adjacent videos captured by a panning camera, anda precise alignment is obtained. Re and Yu performed a coarse-to-frame stitching processfor surveillance applications. The selected frames of two input videos are first dividedinto different layers, and the backgrounds are stitched with a conventional stitching pipelinewhen there are no moving objects across the overlapping regions. Similarly, the matchedfeature pairs are clustered to multiple layers involving different objects, where each layercontains a set of matched feature pairs according to the same homography, and the videosare overall pre-aligned. To avoid missing information, ghosting, and artifacts caused by moving objects, the variations in gradient are calculated in the overlap region, and to further update the optimal seam. Different from the classical process, Jiang and Gu formulateda spatio-temporal mesh optimization framework based on Zhang and Liu's methods.All frames of the input videos are initially aligned according to the estimated spatial andtemporal global transformations, and an objective function is constructed

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to represent thematching costs in the spatial domain and temporal domain, to be solved to improve the geometric alignment. Similar to video texture synthesis, higher weights are assigned to salientregions such as spatial edges and temporal edges, to preserve the salient structures in thevideos and search for an optimal seam.

B. Moving Cameras

Some works focus on stitching videos captured by moving cameras (e.g., a smartphonesor DAVs), which brings stitching additional challenges (i. e., jitters and shakiness). Themethods such as can remove jittery and shaky motions, but cannot be directly applied tostabilize the stitched videos. To solve the jitter in the stitched video, many researchesgenerally perform image stitching and stabilization simultaneously. Guo et al. simultaneously performed video stitching and stabilization. Two transformations were estimated, i.e.,the inter-transformation between different cameras to obtain the spatial alignment, and theintra-transformation within each video to maintain the temporal smoothness. Meanwhile,a mesh-based warping method is adopted for alignment, and a bundled-paths approach isused as a baseline for video stabilization, to synthesize a smooth virtual camera path. It effectively stitches the scenes with a certain degree of parallax, assuming that the camerastably moves while being limited to a certain degree of freedom, initially enforcing a roughsynchronization, and misalignments are caused by large depth variations and strong motion blur. Su et al. formulated video stitching as solving an objective function consisting of astabilization term and a stitching term, and performed an iterative optimization scheme.Recently, Nie et al. extended the method. The backgrounds of input videos are first identified with a background identification method, and to be stitched, and then a false matchelimination scheme is introduced to reduce mismatches. Finally, a scoring strategy is introduced to evaluate the stabilization quality**[3]**. Lin and Liu combined a dense 3D reconstructionand camera pose estimation technique to stitch videos captured by hand-held cameras. TheCoSLAM system was first adopted to recover 3D camera motions and sparse scene points, reconstructing 3D scenes in the overlapping regions, constructing a smooth virtual camerapath staying in the middle of all the original paths, and then a mesh-based warpingoptimization method called Line-Preserving Video Warp (LPVW) method is adopted tosynthesize the stitched video along the path.

C. Direct Techniques

In direct techniques, all the pixel intensities of the images are compared with each other. This technique use cost functions to minimize the sum of absolute differences between overlapping pixels. This technique is computationally complex as there is a need to compare each pixel window to others**[4]**. They are variant to image scaling and rotation. There are many techniques for solving stitching problems using direct methods such as Fourier analysis techniques. It has the advantage that they make use of the information available in image alignment as well as the biggest disadvantage is that they have a limited range of convergence.

D. Feature Based Techniques

It establish the correspondences between points, lines, edges, corners, or other geometric entities. Characteristics of robust detectors include invariant to image noise, scale invariant, translation invariant, and rotation transformations.The two ways to identify thematching region from the input images are Block matching and feature-point matching**[4]**.Block matching algorithms initially calculate the correlation between the regularized blocksgenerated in sequential consecutive images in the set. It can be done either by NormalizedCross-Correlation or by phase correlation using an Fast Fourier Transform. Such methodsinvolve a series of complex calculations and also very sensitive to the slight difference between the images. Feature based methods **[4]** extract different features from each image andmatches these features to establish a global correspondence between all the images. Featuredescriptors are used to extract the features points from the given images for matching itwith other images.There are many feature detector techniques, such as, SIFT , SURF , FAST(Features from Accelerated Segment Test Technique) etc.Feature based methods are robust and potentially faster.

V. VIDEO STITCHING BASED ON FEATURE BASED TECHNIQUES

In this section, a video stitching model based on feature based techniques will be discussed. As shown in Fig. 2, the image stitching model consists of different stages: preprocessing, feature extraction and matching,

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Website: www.ijircce.com

Vol. 7, Issue 12, December 2019

homographyestimation, global alignment, stitching and blending. In the following subsections, the different stages of feature based techniques will be described in detail.

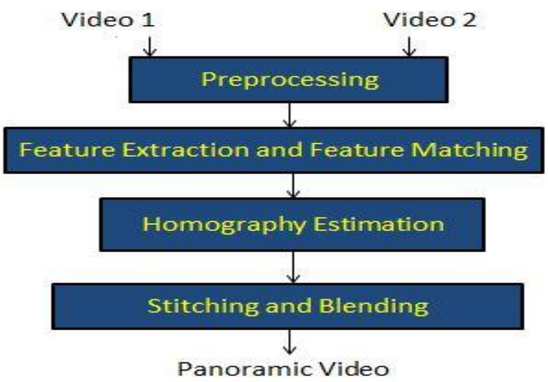

Figure 2: The block diagram of general panoramic video stitching model based feature based approaches

A. Preprocessing

The first stage of any vision system is the video acquisition stage. Video acquisition can be broadly defined as the action of retrieving a video from some sources. Typically, videos can be acquired for panoramic imaging by three different methods, as shown in Fig. 3. Camera can be translated parallel to the scene, and can be rotated or can used handheld devices like mobile phones. In preprocessing, the videos captured needs to be converted into frames of equal resolution.

Figure 4: Videos converted to frames

B. Feature Extraction and Matching

After pre-processing, each frame undergoes feature extraction and matching .There are many feature extraction and matching methods like SIFT, SURF, ORB, FAST, BRIEF etc**[4]**. The keypoints of objects are first extracted from a set of reference images and stored in a database. When a new object is detected, compare each feature of the new object with the database and find candidate matching features by Euclidean distance.Feature detection plays an important role of many computer vision algorithms.Online image processing algorithms need real-time performance. Thus the speed at which features are detected is crucial in many applications, such as visual SLAM (Simultaneous localization and mapping), image registration , 3D reconstruction, and video stabilization so that there is a corresponding match between features and multiple views. The feature points need to be described unambiguously so that the correspondence between multiple views can be computed reliably. Corner points needs to be matched along with other features so to give quantitative measurement.Corners are good features to match. The corner features are more stable over changes of viewpoint and if there is a corner in an image then its neighborhood will show an abrupt change in intensity.

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C. Color Descriptors

Histogram is defined as the distribution of the number of pixels in the image. The number of elements in a histogram is related to the number of bits in each pixel of the same image. The histogram which is a combination of three 1D histograms of the RGB color space called RGB histogram. This histogram having no invariance properties. Opponent histogram is a combination of three 1D histograms of the channels of the opponent color space. In the HSV color space, near the gray axis the hue is unstable. By weighing each sample of the hue by its saturation the hue histogram can be made more robust . With respect to light intensity H color model is shift and scale-invariant . The chromaticity components describe the color information of the image in the normalized RGB color model. The chromaticity component thus invariant to light intensity changes, shadows, and shading. An RGB histogram is not invariant to light changes. With respect to light intensity by the pixel value normalization, scale and shift invariance is achieved. Color Coherent Vector each histogram bin is partitioned into two types: coherent and incoherent. Coherent type contains pixel values of the images that belongs to a large informally colored region of the image. Otherwise it is incoherent type. Color histogram does not contain the spatial information of pixels thus similar color distribution for different images results. Color moments uses all the generalized color moments up to the second degree of the histogram bin and the first order results in nine combinations. It gives a total 24 color moment invariant. Color SIFT Descriptors is aimed to describe the local shape of a region by edge orientation histograms. The gradient of an image is possibly shift-invariant. Due to changes in light intensity , the direction of the gradient and relative gradient magnitude will be same.The SIFT descriptor is variant to light color changes, because the R, G and B channels are combined to form the intensity channel.

D. Texture Descriptors

Texture can be a very useful feature in browsing, searching and retrieval of images . The properties such as smoothness, coarseness, and regularity is provided. Texture properties can be measured statistical, structural and spectral method. GLCM(gray level co-occurrence matrix) is the most known texture descriptors . Angular Second Moment, which is the sum of squares of entries in the GLCM and measures the image homogeneity. When image has very good homogeneity or when pixels are very similar, angular second moment is high. Inverse Difference Moment (IDM) is the local homogeneity which is high when local gray level is uniform and inverse GLCM is high. Entropy will show the amount of information of the image which is needed for image compression. The loss of information or message in a transmitted signal can be measured using entropy. Correlation can measure the linear dependency of grey levels of neighboring pixels. At the time of RGB to GRAY level conversionof an image, extract the features with GLCM approach so that the image compression time can be greatly reduced. GLCM is used for the motion estimation of images, it can be used to extract second order statistical texture features from the images. The four features such as Angular second moment, correlation**[4]**, Inverse difference moment and Entropy are computed in GLCM texture extraction. Haralick Texture Feature captures the information about the patterns that created in patterns of texture of the image. Haralick features are calculated by using co-occurrence matrix, which is computationally expensive in real time application.

E. Visual Descriptors

Visual color descriptors are used to extract color features of the image that are not robust to the changes in the background colors and are independent of orientation and size of image. It can be used for distinguish still and moving images. Visual texture descriptors extract textures which contains the visual patterns of the set of images that have the properties of homogeneity of texture . It contains important structural information of surfaces of the objects in the image and their relationship to the surrounding environment. Visual shape descriptors extracts the shape of image objects which provides a useful hint for similarity matching between different objects. For image retrieval the shape descriptor wants to be invariant to scaling, rotation and translation transformations.

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F. Frequency Domain Descriptors

There are four computational steps for extracting key points in SIFT. It reduces number of keypoints which helps in increasing the efficiency and also the robustness of the technique. Keypoints are rejected when they had a low contrast or if they were located on an edge. SURF is a fast and robust algorithm used for local**[5],** similarity invariant representation and comparison of the feature points. The main advantage of the SURF approach is its fast computation, provides real-time applications such as tracking and object recognition. In real time frame rate application FAST algorithm is an interest point detector. Around a point a fixed radius of circle is considered and compare the pixels in that region in FAST detector. ORB technique is a fast binary descriptor based on BRIEF. BRIEF uses simple binary tests between pixels in the smoothed image patch of the original image.Over a retinal sampling Fast Retina Key point (FREAK) uses a cascade of binary strings by efficiently comparing pixel intensities of image.

1. Scale Invariant Feature Transform (SIFT) Technique

The most robust and widely used image matching algorithm based on local features is SIFT. It gives a good panoramic image/video and a reliable result. SIFT is one of the feature detection and description technique. To describe the image features, SIFT produces key point descriptors. Mainly there are four computational steps for extracting key points like scale-space peak selection, key-point localization, orientation assignment, and defining key-point descriptors. To each frame, it builds image pyramid by generating progressively blurred out images and to get the difference of Gaussian (DOG) pyramid it subtracts neighbour images. Then, detects the extreme for DOG pyramid. To increase efficiency and robustness the number of keypoints was reduced. If keypoints had low contrast or being located at edges they are rejected. The next step is orientation assignment for which orientation histogram is used with sampling the centerneighborhood of the key points. The last step is to describe the key points.

2. Speeded Up Robust Features(SURF) Techniques

SURF is a fast and robust algorithm developed by Bay for local, similarity invariant representation and comparison**[5].** There are mainly three steps in SURF approach. At distinctive locations in the image, such as corners, blobs, and T-junctions, the keypoints are selected. Next, represent a feature vector at the neighborhood of every keypoint. This descriptor has to be distinctive as well as it should be robust to noise, detection errors, and geometric and photometric deformations. Finally, the descriptor vectors are matched to different images. Fast-Hessian Detector that is based on the approximation of the Hessian matrix is used for finding keypoints. The responses to Haar wavelets are used for orientation assignment before the keypoint descriptor is formed from the wavelet responses in a certain surrounding to the keypoint. A circular region is constructed around the detected keypoints. The main advantage of the SURF approach is fast computation, enabling real-time applications. It is faster than SIFT by keeping in view of the quality of the detected points. It mainly focus on speeding the feature matching. To increase the matching speed, the Hessian matrix is used. The disadvantage is that it is poor at handling viewpoint and illumination changes.

3. Features from Accelerated Segment Test Technique(FAST)

Rosten Drummond introduced FAST for identifying interest points in an image**[6].** To develop an interest point detector for use in real time frame rate applications FAST was introduced. Around a point of fixed radius circle, the FAST detector compares pixels. A point is classified as a corner only if one can find a large set of pixels on a circle of fixed radius around the point are all significantly brighter or darker than the central point. The disadvantage of FAST detector is that multiple features are detected adjacent to one another. When a set of n contiguous pixels in the circle are all brighter or darker than the candidate pixel, an interest point is indicated.In the first step, if there exist at least n consecutive circle pixels, the center pixel p is labeled as corner. At least three of the four pixel values – I_1 ,I_5 ,I_9 ,I_{13} should be above or below I_P + T, then p is considered as a corner. In this case, eliminate pixel p as a possible interest point. If there exists at least three of the pixels above or below Ip + T, then check all 1_6 pixels and check if 1_2 contiguous pixels fall in this criterion. Repeat this same for all the pixels.

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4. Oriented Fast And Rotated BRIEF Technique(ORB)

Based on Binary Robust Independent Elementary Features (BRIEF) key point descriptor, ORB is a very fast binary descriptor. There are several advantages for binary based features over vector based features. They are faster in computation, more compact in storing, more efficient in comparing, and requires very low memory. Many experiments are demonstrated in showing how ORB is at two orders of magnitude faster than SIFT. The efficiency of ORB is tested on some of the real-world applications, including object detection and patch-tracking on a smart phone**[6].**A multi-scale Harris keypoint and oriented patch descriptor was proposed. ORB builds based on FAST keypoint detector and recently developed BRIEF descriptor. Both these techniques are attractive based on their good performance and low cost. For better performance in nearest-neighbour applications, ORB uses learning method for de-correlating BRIEF features under rotational invariance.

5. Binary Robust Independent Elementary Features(BRIEF) Technique

BRIEF provides a shortcut to find the binary strings directly without finding descriptors. Selects a set of n_d(x,y) location pairs in an unique way, and uses a smoothenes image patch. Pixel intensity comparisons are done on location pairs. Consider first location pairs be p and q. If I(p)<I(q), then its result is 1, else it is 0. This is applied for all the n_d location pairs to get an$_d$-dimensional bitstring. This $n_d$can be 128,256 or 512. BRIEF is a faster method for feature descriptor and matching.

6. Fast Retina Keypoints(FREAK) Technique

FREAK is a retina-inspired keypoint descriptor. FREAK enhances the performance of current image descriptors. It is simple and outperforms recent state-of-the-art. A cascade of binary strings is computed by efficiently comparing pairs of image intensities over a retinal sampling pattern. Interestingly, selecting pairs to reduce the dimensionality of the descriptor yields a highly structured pattern that mimics the saccadic search of the human eyes. FREAK is faster than BRISK.

C. Homography Estimation

Homography is a transformation that maps the points in one image to the corresponding points in the other image. To remove outliers, estimate the homography transformation from the feature points.There are different methods for homography estimation likeDLT**(**Direct Linear Transform),Cost functions, RANSAC(Random Sample Consensus)and LMS(Least Median Square)etc.After extracting features and matching them, outlier elimination needs to be done. For eliminating outliers one of the method is Random Sample Consensus(RANSAC). It means that 2 features in the images don't correspond to same real world feature at all. RANSAC is a non-deterministic algorithm and produces an accurate result only with a certain probability. In 1981, Fischler and Bolles published RANSAC algorithm.

D. Stitching and Blending

Stitching is used to combine the two images in the data set and producing the resultantpanorama.Comparing the pixels is used to combine the images . There is seam when twoimages are overlapped, creates ghosts, ghosts can also occur when there is moving objects in the scene.The aim of the image stitching algorithm is create a seamless panorama. The seam in betweenthe images is invisible. Alpha blending is used to blend two images. Alpha blending is basedon pixels with mixed colors, a measurement is needed to weight the influence of differentelements**[7].** At the stitching line, the weight is half and half, while away from the stitchingline one image is given more weights than the other. Alpha blending will merge two images seamlessly. However, ifthe images are not aligned well, the disagreements will show in the blended image.

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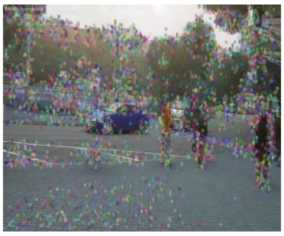
VI. RESULTS AND ANALYSIS

Frame 1

a) Using SIFT

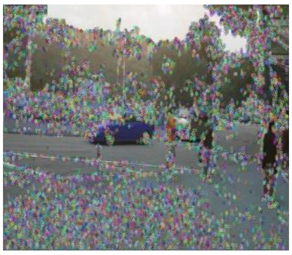


b) Using SURF

c) Using ORB

d) Using BRIEF

e) Using FREAK



f) Using FAST

g) Using DAISY

h) Using VGG

i) Using STAR

Figure.5: Result of various feature extraction methods

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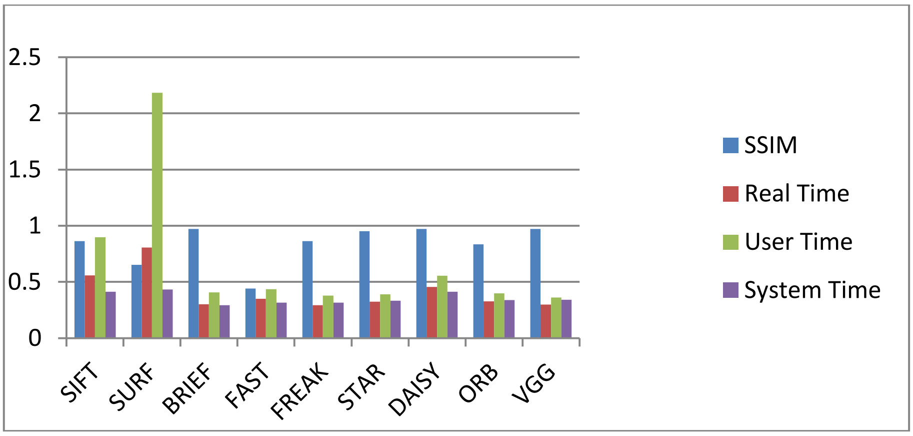

Fig. 6 : Comparison of various feature extraction methods based on SSIM(Structural similarity index measurement), Real Time, User Time, System Time

Table I:PERFORMANCE EVALUATION OF DIFFERENT FEATURE EXTRACTION METHODS

Methods	Real time	User Time	System Time	SSIM
SIFT	0.558	0.896	0.412	0.8627
SURF	0.806	2.183	0.433	0.6507
BRIEF	0.302	0.406	0.294	0.9716
FAST	0.349	0.434	0.315	0.4396
FREAK	0.294	0.377	0.314	0.8627
STAR	0.323	0.391	0.332	0.9517
DAISY	0.455	0.555	0.411	0.9716
ORB	0.328	0.399	0.339	0.8344
VGG	0.299	0.360	0.340	0.9716

VII. CONCLUSION

Video stitching attracts less attention than image stitching, probably owing to their relationship: they are both similar and different. Video stitching in many ways is an extension of image stitching, and large degrees of independent motion, camera zoom, and the desire to visualize dynamic events impose additional challenges, i.e., parallax and ghost effect.The unfixed optical centers of cameras and objects moving across cameras are the challenges to video stitching. Besides, parallax problem exists when objects are close to cameras. Therefore, video stitching is a challenging task. Another challenge is that projective transformation usually produces shape distortion in non-overlapping regions, which cause wrong depth perception to the viewer. The other diffculity is that exposures for images captured by different cameras may be inconsistent due to different light directions, thus making the video stitching more challenging.One challenge in video stitching under this circumstance is that videos captured by moving cameras often appear shaky[8].It has many application in virtual reality,tourism, gaming etc.

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