Real-Time Image and Video Stitching Via Seamless Integration of Live Camera Feeds for Enhanced Visual Quality

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Real-Time Image and Video Stitching Via Seamless Integration of Live Camera Feeds for Enhanced Visual Quality

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Abstract Computer vision techniques for aligning and fusing images have long been employed to create smooth photographic mosaics. These methods have found applications in image stabilization features of camcorders, production of digital maps and satellite images through high-resolution photographic mosaics, and more. This paper introduces a novel method for generating composites from two or more images, with the ability to significantly reduce or eliminate white space when operating with a live connection. By leveraging algorithms such as Scale-Invariant Feature Transform (SIFT), the proposed method enables feature recognition and extraction from captured images, facilitating the removal of white space in live images. Additionally, this work presents a technique that merges live images with real-time camera input to complete missing elements by intelligently manipulating controlled elements in the images. The resulting approach offers a promising solution for real-time image fusion and the seamless integration of live camera feeds, enhancing the visual quality and completeness of the final composite.

Keywords: Computer vision techniques, Photographic mosaics, Image stitching algorithms, SIFT (Scale-Invariant Feature Transform), Real-time camera merging

1. Introduction

Image Stitching is a technique used to integrate many pictures into a single panoramic image. The fundamental difficulty in image stitching is aligning and flawlessly blending the overlapping areas between neighbouring photographs to produce a panorama that looks natural. The issue can be stated in the following way:

Given a collection of N input images (I1, I2, IN), along with the corresponding camera settings (P1, P2, PN), Pi = K, R, t represents the intrinsic matrix, rotation matrix, and translation vector of the camera that took the i^{th} image, respectively. The objective is to create a panoramic image P with a natural-looking appearance that fully captures the scene shown in the input photographs.

Important concepts involved in the formulation of the image stitching problems are Feature Detection, Feature Matching, and Estimation of Homography, Image wrapping and Blending.

Feature Detection is finding distinguishing elements in each image, such as corners or edges, through the process of feature detection. Feature matching is the process of matching features between different photographs. Estimation of Homography is the calculation of the transformation matrix that maps the characteristics of one image onto the other is the process of estimating homography. Image warping is the process of changing the viewpoint of one image to match another. Blending is the seamless blending of the images. Vanishing artefacts are produced when the overlapping pixels are simply averaged.

360^0 Image Generation uses a collection of 2D images taken at various angles, 360^0 image production aims to produce a three-dimensional model of an object or scene. The problem involves estimating the depth and geometry of the scene from the 2D images and synthesizing a 3D model. The issue can be stated in the following way:

Using a set of N input photos (I1, I2, IN) and their associated camera parameters (P1, P2, PN), the goal is to rebuild a 360^0 model M of the scenario that was recorded by the input shots. The solution should create an accurate 360^0 model of the scene by synthesizing the depth and geometry of the scene from the input photos. Occlusions, reflections, and other problematic elements that could impair the quality of the 360^0 model should also be handled by the solution.

The objective is to infer the scene's 3D structure from the 2D photos. Techniques like structure from motion (SFM) or multi-view stereo can be used for this (MVS).

The photos can be reprojected onto the 3D model after the 3D structure has been predicted to create a 360^0 image of the scene. For these jobs, Python libraries like PyTorch and OpenCV can be employed.

Important concepts involved in the formulation of the 3D picture generating problem are Camera Calibration, Feature Detection, Feature Matching, Traingulation, Surface Reconstruction and Texture Mapping.

Camera Calibration is the process of calculating a camera's parameters to take photos .Feature Detection is to find distinct features in each image. Feature Matching is the process of matching features between different photographs. Traingulation is to find the 3D location of the matching features in space by triangulation. Surface Reconstruction is the process of making a surface mesh from the triangulated points is known as surface reconstruction and Texture Mapping is adding the colors and textures from the original photos to the surface mesh.

Video stitching is a technique used to combine several video frames taken from several cameras or perspectives into a single panoramic video. By processing several frames in real-time, the issue is analogous to image stitching. The issue can be stated in the following way:

The objective is to create a single panoramic video stream V that encompasses the whole scene taken by the input streams and has a natural-looking appearance given a set of N video streams (V1, V2,..., VN) shot from various angles. The answer must support both real-time video input and output. Similar to image stitching, video stitching presents the same set of challenges, with the extra difficulty of controlling temporal changes between frames.

Important concepts involved in the formulation of the video Stitching is Feature Detection, Feature matching, Estimation of Homography, Picture warping, Temporal Alignment and Blending. Feature Detection: Finding distinguishing features in each frame through feature detection. Feature Matching: Feature matching is the process of matching features between frames. Estimation of Homography is to determine the transformation matrix that maps the characteristics of one frame onto the other. Picture warping is the process of altering the perspective of one frame to match another. Temporal Alignment is the process of adjusting the timing of the frames to produce a smooth transition is known as temporal alignment and Blending is the flawless blending of the frames.

Algorithms for creating panoramas have been created in the past and put into use numerous times. Several algorithms have been enhanced to function on mobile processors in real-time applications. The classification of data into distinct groups based on shared characteristics has been done using various well-known machine learning concepts. Panorama stitching is the technique that includes blurring and injection between pixels for a higher quality final image, as well as geometrical methods of image recognition utilizing camera matrices and the creation of a hologram (way to produce 3D images) between two images. For image alignment and stitching, direct and characteristic-based procedures are the most common. Using all the information in an image, the direct technique is a brute force approach. It is more precise since it incorporates all of the information at hand, but it needs input from an individual to identify the matched image pairs. In terms of computing, it is also considerably slower. The feature-based approach doesn't involve user input because it focuses on automatically matching certain spots in an image and relies on the surrounding areas of the image to be constant[1-3].

The proposed methodology automates image sorting and panorama stitching using an approach based on invariant features called Scale-invariant feature transform (SIFT). SIFT technique enables accurate image matching throughout the image database irrespective of camera zooming, rotation, and lighting. Proposed method clusters images in an image database based on relationships and employs SIFT, key point matching, Random Sample Consensus (RANSAC).The panorama picture collections are then linearly stitched together.

The objective of this research is to provide proper and more intuitive way of stitching two or more overlapping images into one image with high resolution pixels. Also helps in designing 3D models from multiple images for fulfilling multiple purposes.

2. Literature Review

Researchers have made significant contributions to the field of image and video stitching by proposing various techniques and algorithms. For instance, Harrison Chau and Robert Karol[4] introduced the use of machine learning and computer vision algorithms for image stitching, utilizing clustering techniques and mosaic creation to generate panoramas. However, challenges arise when dealing with cluttered environments and blurry frames caused by motion and insufficient overlap. Anant Levin et al.[5] focused on assessing image quality and minimizing seams using formal cost functions based on the gradient domain. Nonetheless, geometric misalignment due to lens distortion remains a concern. Ebtsam Adel et al.[6] explored two main techniques: direct and feature-based, with the latter proving advantageous. However, noise in images and the need for efficient processing in large image collections pose challenges. Wei Lyu et al.[7] extended image stitching to video stitching, employing pixel-based, gradient-domain, depth-based, and feature-based methods. Yet, issues such as parallax, exposure differences, and angle variations persist. Siddique Abu Bakar et al.[8] applied image stitching to digital chest radiography, addressing the limitations of a flat plate system. However, testing under varying conditions and lighting remained a challenge.

Kaimo Lin, Nianjuan Jiang et al.[9] tackled image stitching with large parallax by introducing a method that reduces visual artifacts caused by misalignment, known as parallax. Wei Jiang and Jinwei Gu[10] focused on stitching multiple synchronized video streams, resolving issues related to temporal coherence and foreground object motion. However, disparities in video stitching remained unaddressed. Michael S. Brown et al.[11] proposed the Moving Direct Linear Transformation (Moving DLT) method, which effectively bridges incompatible portions of images and achieves high-precision stitching with minimal ghosting. Fan Zhang and Feng Liu[12] introduced a local stitching technique that manages disparity and only requires perfect alignment in specific regions. However, the alignment of images across the overlapping region was less critical. Chen et al.[13] highlighted the importance of image acquisition, registration, and merging in creating panoramic images, with applications in various fields. The use of dictionaries and linear camera arrays, as proposed by Wei-Sheng Lail et al.[14], demonstrated effective solutions for addressing parallax and increasing the field of view. Additionally, the Speeded Up Robust Features (SURF) algorithm emerged as a reliable method for local image encoding and comparison, offering real-time applications. Lastly, Julio Zaragoza et al.[15] introduced warps that combine projective and non-projective variances to accommodate imaging variations, integrating the Moving DLT method for accurate estimation. Various methods as suggested in existing research work in the field of image stitching is shown in the Table 1.

Table 1. Existing methods for contrasting in image stitching used

Author	Key concepts used	Merits	Demerits
Harrison Chau and Robert Karol [4]	Use of Machine learning and computer vision algorithms.	Automated stitching with ML and computer vision improves efficiency and enables seamless panoramas.	Challenges with cluttered environments, motion blur, and minimal overlap in photos.
Anant Levin, Assaf Zomet, Shmuel Peleg, and Yasir Weiss [5]	Measuring image resemblance, seam visibility, and introducing cost functions for image stitching.	Improved stitching with measured resemblance, visible seams, and formal cost functions.	Geometric misalignment due to lens distortion caused by moving objects is a drawback of this approach.
Ebtsam Adel, Mohammad Elmogy, and Hazem Elbakry [6]	Two techniques for image stitching - direct method and feature-based method	Feature-based approach offers advantages over the direct method, determining image relationships through specific features extracted from processed images.	Noisy images can affect feature extraction, indexing is required for efficiency in large image collections, and perfect sight seams are necessary.
Peleg et al. [7]	Optical flow	Allows pre-processing and address the accumulating error quickly.	Poor precision with no parallax, and no stabilization.
Levin et al. [8]	Gradient weighting	Seamless in nature.	Input alignment of images.
Kaimo Lin, Nianjuan Jiang, Loong-Fah Cheong1, Minh Do and Jiangbo Lu [9]	Large parallax and the use of RANSAC for homography.	Addressing the challenge of stitching images with large parallax and utilizing RANSAC for accurate homography.	Homographic transformations can introduce visual artifacts and misalignments (parallax) in the stitched images.
Jiang and Gu [10]	Spatiotemporal mesh optimization.	Align the geometry better.	Difficult to calculate.
Michael S. Brown, Tat-Jun Chin, and Julio Zaragoza [11]	Moving direct linear transformation enhancing fit using data-driven strategies.	Moving DLT seamlessly bridges projection model-incompatible portions of the image, achieving high-precision stitching with minimal ghosting effect.	Traditional methods often result in misalignment and ghosting, which are addressed in this study by employing different strategies and data-driven fitting techniques.

Zhang, Fan and Liu [12]	Simple Sparse feature matching.	Automatic in nature.	Only applicable to single plane.
Chen, Yen and Klette[13]	Dual homograph is used.	Two planes are used.	Single homograph is used.
Wei-Sheng Lail, Orazio Ga, Jinwei Gu, Deqing Sun, Ming-Hsuan Yangl, and Jan Kautz[14]	Video stitching using a dictionary as a linear array and addressing the challenge of parallax.	Linear camera array for CNN based stitching.	No demerits mentioned in the given paragraph.
Oyanllon, Edouard and Rabin [15]	Multi-affine	Address small parallax.	Single affine with no preprocessing, and no stabilization.
Peleg, Rousso and Zomet [16]	Mesh-based	Multiple transformations are present.	Local distortion with no preprocessing, and stabilization.
He and Yu [17]	Layer stitching	Accurate alignment is there.	Difficult to calculate.
Uyttendaele et al. [18]	Graph structure	Reduce ghosting brought on by moving items.	Difficult calculation with no pre-processing, no parallax, and no stabilization.
Nie, Su, Zhang and Sun [19]	Optimization function	Stabilization and stitching should be balanced.	Difficult to calculate with no preprocessing, and no parallax.
Su, Nie, Sun, Li[20]	Discriminatively stitching the videos between backgrounds and foregrounds	Stabilization and Improve the matching in computer vision.	Difficult to calculate with no parallax, and no pre-processing.
Lin et al. [21]	Estimate parameters of the cameras	Stabilization and calculate the 3D camera trajectories with precision.	Only applies to continuous, in-depth videos with no parallax, and no preprocessing
Zhi and Cooperstock [22]	Depth and color.	Address a specific depth discontinuity.	Difficult calculation with no preprocessing, no parallax, and no stabilization.
Liu and Chin [23]	Inert more appropriate correspondence based on pixels.	Address the images with wide-baseline and a particular amount of parallax.	Difficult in calculation.
Chang et al. [24]	Local hybrid transformation model	Different transformations between over-lapping and non-overlapping regions.	Limited to images that are vertical or parallel.
Li, Xu and Wang [25]	Scam-driven	Improving seam and minimizing ghosting and a particular amount of parallax.	Repetitive processes and challenging calculations with no pre-processing, and no stabilization.
Hermann et al. [26]	Prior constraints	Address the moving object-containing images separately.	Restricted to pictures with detectable objects.
Guo et al. [27]	Spatiotemporal alignment	Use some parallax while addressing the scenes with stabilization.	Restricted to the cameras with a specific level of latitude and demand processing beforehand.
Li, Xu and Wang [28]	Quasi homography	Reduce distortion is there.	Limited to parallel images.

Zhang and Liu [29]	Hypotheses of warping	Strong and efficient stitching and a particular amount of parallax.	Alignment knowledge's cannot be reused with no preprocessing, and no stabilization.
Chen and Chuang [30]	Coarse-to-fine scheme	Adjustment for rotation and scale and a particular amount of parallax.	Specific distortion with no preprocessing, and no stabilization.
Zhang, He , Chen, Jia and Bao [31]	Various prior and constraints optimization terms	Look at the wide-baseline photos.	Calculation difficulty and regional distortion.
Xiang, Xia, Bia and Zhang[32]	High-level features	Deal with the pictures that have a particular amount of low texture.	Specific distortion.
Rav-Acha et al. [33]	Embed the detected objects into the stitched Backgrounds.	Accurate alignment is present.	Limited to the videos captured by a panning camera.

Nie, Lang, et al.[34)] proposed a two-stage unsupervised coarse image alignment and unsupervised image reconstruction system for unsupervised deep image stitching.

Lai, Wei-Sheng, et al.[35)] provide a unique pushbroom stitching network and a quick pushbroom interpolation layer that learns a dense flow field to cleanly align the numerous input videos for spatial interpolation..

These advancements in image and video stitching techniques continue to drive research efforts towards achieving high-quality results with improved efficiency in various applications as suggested by different researchers[36-41)].

3. Proposed Methodology

Development of the proposed method consists of three 3 phases -2D Panorama stitching, 3600 view and Real time video stitching.

3.1 2D Panorama Stitching

The first stage was to find out whether two or more images can be combined or not. To create a fragmented panorama or high-resolution image, many images with overlapping areas of view or points of view must be combined. To achieve consistent results, the image stitching process needs nearly exact image matches and identical exposures also called as 'Mosaic Images'. The act of joining two or more photos to produce a single, enormous image is referred to as "stitching" in its own right. Figure 1 illustrates the various procedures used to create panoramic photos for image stitching.

Fig .1: Steps involved in general panoramic image stitching.

Image Acquisition is the initial step. It is possible to define this as a process that extracts a picture from a given source. These methods entail moving the camera plumb and vertical to the subject matter, keeping the optical centre constant, or utilizing a portable device that rotates around the vertical axis as shown in Figure 2.

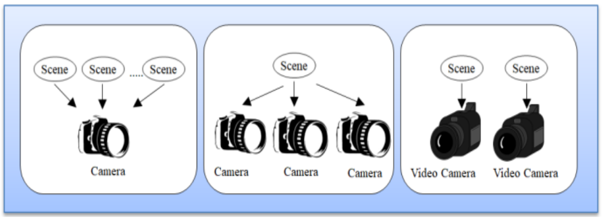

Fig.2: Various ways of image acquisition.

Features Detection and Matching is considered as the basic level of image stitching. The factors must be matched within the image or within the larger image, so the features can be explained. It is based on the idea that, rather than scanning the entire image, it is highly helpful to pick out a few distinctive features and carefully assess those points. The bureaucracy of feature detection plays a significant role in many computer vision techniques. To accurately calculate correspondences between different perspectives, it is necessary to define detected corners or other distinguishing features. Faster feature recognition, description, and assignment are necessary for real-time processing. Corners can be adjusted to offer quantitative measures for more accurate feature matching between picture pairs. Corner is a real customising ability. Adjusting the seeing angle is less steady than angular ability. The second most significant aspect of corners is when they appear abruptly extra-deep in images with corners. On the other hand, proximity feature descriptors define pixels (or locations) inside a picture based on their proximity content. They have the potential to locate matching pixel locations in images that represent the same set of facts, such as spatial depth, under particular circumstances. They are thought to be resistant against minor deformations and localization mistakes. For instance, among other constraints, near feature detectors must be invariant to translations, rotations, scaling, affine transformations, and blurring. It ought to be impervious to obstruction, mess, and variations in illumination. It must be iterate as well. Finally, there must be enough components to efficiently symbolize the image. There are numerous skill descriptions, including PCA-SIFT, SURF, HOG, and GLOH.

RANSAC is used to calculate the homography's mathematical parameters from a set number of localised statistics with iterative outlines as matching is performed for all images based on feature statistics. The image matching step finds which image is adjacent to another image and finds the efficient feature match set needed in the next step for all feature match sets. Figure 3 shows matching of key points and inliers using RANSAC.

Fig. 3: Key point and inlier matching using RANSAC.

Global Alignment is the approach that is most appropriate in bundle fitting. It is a photogrammetry technology that creates a precise 3D reconstruction by combining many photographs of the same scene. This step's goal is to identify a set of alignment parameters that are universally consistent and minimise miss-registration between all picture pairings. It is important to initially compute a preliminary estimation of the 3D coordinates of the scene's features, just like when estimating camera positions.

Compositing is done once all the input images are registered, there is needed to get the final result as a composite image. For this, selection of the final composition area is done. Once all the images are fully registered, merging images is needed. There are numerous sorts of pixel blending techniques, including image pyramid blending, gradient domain, and feathering.

Although there are other factors that can indicate how well a picture has been stitched, the level at which the final product matches each of the original photos and how clearly the seams are seen are the two main ones. To define and produce the best possible stitches, cost functions are employed to evaluate stitch quality. To eliminate spurious edges along seams, these cost functions assess how similar the input and output images are as well as how obvious seams are in the gradient domain.

3.2 Creation of 360^0 view

Second phase in the proposed method is to create a 360^0 view of the created panoramic shot using image stitching algorithm as described in first phase. The resulting image overlays the stitched image in 360^0 and can scroll through that image to make it more realistic. The steps shown in Figure 4 are used to create a 360^0 view of an image.

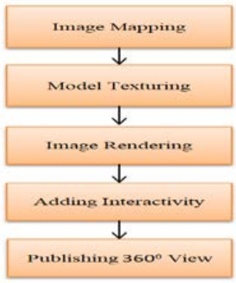

Fig. 4: Steps followed in creation of 360^0 view.

To achieve the 360^0 view, the panoramic image must be mapped onto a sphere or cylinder. This can be done using various techniques, including manual sculpting, photogrammetry, or scanning. To give the model mapping a realistic appearance, it must be textured after being constructed. Applying pictures, textures, and other elements to the model's surface is known as texturing. The model must be rendered into an image space once it has been lighted, textured, and rendered. In order to do this, a rendering engine must produce a stunning representation of the 360^0 model. More interfaces are needed in order to give consumers the ability to interact with the 360^0 view. It might be a graphic user interface or a web browser. Lastly, a website or other platform can post the 360^0 view, enabling users to view and interact with the image in 360 degrees.

3.3 Real time video stitching

A common and well-liked feature of such devices is the ability to combine groups of images from various perspectives into a complete panoramic image. Capturing of frames in real time by extending this feature to video stitching can be done. The technical and practical challenges of combining the entire high-definition multi-view video into a high-definition panoramic video have been examined. Although it is not possible to link moving frames directly, it can try when the targets are static. Multiple wireless cameras for covering every position in the room in real-time, and the proposed method link every frame captured by each camera in real-time. The resulting merged frame includes all the sites captured by the cameras. Using this method, a complete view of the site for monitoring purposes is created.

Algorithm for Image Stitching:
Input: Set of N images to be stitched together.
Output: Stitched image.

1. Initialize an empty canvas to hold the stitched image.
2. For each pair of adjacent images (image1 and image2) in the set:
   a. Detect and extract keypoints from image1 using a feature detection algorithm (e.g., SIFT, SURF, ORB).
   b. Compute descriptors for the keypoints in image1.
   c. Detect and extract keypoints from image2.
   d. Compute descriptors for the keypoints in image2.
   e. Match the corresponding keypoints between image1 and image2 using a feature matching algorithm (e.g., FLANN, brute-force matching, RANSAC).
   f. Use the matched keypoints to estimate a homography matrix H that describes the transformation between image1 and image2.
   g. Apply the perspective transformation using H to warp image1 to align with image2.
   h. Blend the warped image1 with image2 to create a composite image.
   i. Update the canvas by appending the composite image.
3. Repeat step 2 for all adjacent image pairs until all images are stitched together.
4. Apply any necessary image blending or feathering techniques to ensure smooth transitions between the stitched images.
5. Return the final stitched image.

4. Results and Discussion

The images that are shown in Figure 5 are a series of images combined that we have to convert into a 2D panoramic image using the current algorithm. The database contains images that are shown in the Figure 5.

Fig.5: Series of images.

Based on image matches, the algorithm organizes these images into folders. Figure 6 shows the keypoint matching connections.

Fig. 6: Keypoints extraction and matching

Next, similar images are stitched together using the connected components, which are the key points of the images, to output a panorama. Figure 7 shows the output panaroma based on proposed algorithm.

Fig.7: 2D Panorama Stitching.

Once the panorama is created, it shows a 360^0 view of the stitched images as shown in Figure 8. This can be viewed both vertically and horizontally by simply panning the image. This algorithm takes the image obtained by stitching the images together and transforms it into a 3D view that can be viewed in 360^0.

Fig.8: 360^0 View of stitched image.

Figure 9 displays real-time images with the first camera's coverage of the left portion of the final frame. Figure 10 displays the real-time images with the second camera capturing the right portion of the final frame.

Fig.9: Real-time video of left side of camera.

Fig.10: Real-time video of right side of camera.

The image shown in Figure 11 shows the grayscaling of these two frames and key point matching.

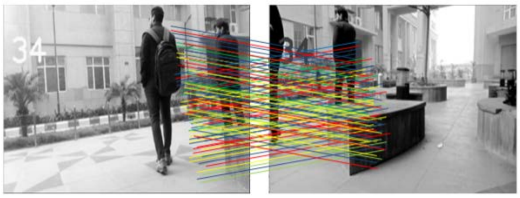

Fig.11: Keypoints detection and matching of frames.

Once the keypoints is detected then the final result with real-time object detection and frame rate of the resulting image. Basically, the algorithm used the connected components of both camera and frame keypoints, and the video panorama was output by merging similar frames. An object detection method is used for identification of spotted person by confidence rate.

Fig.12: Final stitched video output.

In Figure 13, the camera is taking 60 images in a single second, each snapshot freezing a moment in time with utmost precision. This rapid succession of images allows the camera to capture even the most fleeting movements. Images captured at 1/60 second intervals are combined which results in a fluid representation with respect to time.

Fig.13: Capturing Images at 1/60 Second Intervals.

The process to create seamless narrative of images begins with selecting a reference point in the first image. As subsequent images are captured, the software analyzes overlapping regions and aligns them to the reference point. Each image contributes to the final composite, and the result is a captivating visual story that seamlessly illustrates the progression of time as shown in Figure 14.

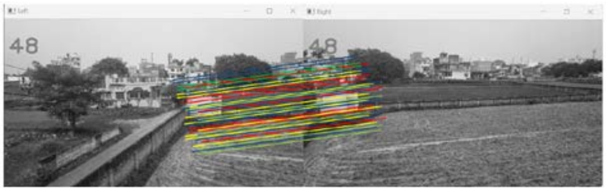

Fig.14: Creating Seamless Narrative.

The final composite image is a testament to the camera's ability to capture an incredible level of detail and movement. The stitched image provides viewers with a unique perspective, as if time has been condensed into a single frame. It's a testament to both the technological prowess of modern cameras and the creativity of photographers who harness these capabilities. The process of stitching images captured at 1/60 second intervals comes together seamlessly, resulting in a captivating visual stream where each frame flows in real-time without any latency or delay as shown in Figure 15.

Fig.15: Final Composite Image.

4. Conclusion

The computer vision techniques for aligning and fusing images to produce smooth photographic mosaics are among the earliest and most well-known in the field. Any camcorder with an "image stabilization" feature employs frame rate image smoothing. Today's digital maps and satellite images are produced using high-resolution photographic mosaics made by image stitching algorithms. In this paper, proposed method can generate composite of two or more images. However, with a live connection, the white space is reduced to 0%. Algorithms such as SIFT can recognize and extract features from captured images. After setting the key points, Remove the white space in the live image is eased. In this work, a method of merging live images with a real-time camera to complete missing elements by inverting controlled elements in the images is suggested.

In the future, the range of system implementations can be expanded by connecting sensors to all possible real-time environments. The system can be trained dynamically to recognize and extract various environmental features in real time. This allows for closer follow-up and monitoring. Implementing this system for surveillance, recording, live video transmission, etc. can be the ultimate step in image stitching.

In the upcoming years, it is anticipated that the fields of picture stitching, video stitching, and 3600 image creation would advance quickly. The following are some potential directions for these technologies' growth and development:

- **Enhanced software and algorithms**: The functioning of picture stitching, video stitching, and 360^0 image building primarily depends on sophisticated algorithms and software. More complex algorithms and software will be made possible by developments in machine learning and computer vision, allowing for quicker and more accurate stitching and construction.

The process of stitching images captured at 1/60 second intervals comes together seamlessly, resulting in a captivating visual stream where each frame flows in real-time without any latency or delay. As the images are rapidly captured and meticulously stitched, the composite image evolves naturally, creating an uninterrupted narrative that beautifully encapsulates the passage of time, movements, and moments, all unfolding fluidly and instantly to the viewer's eye.

The speed, usability, and image quality of video stitching technologies are all anticipated to significantly improve in the future. Here are a few suggested directions for improvement:

- **High-resolution stitching:** As cameras continue to improve, video stitching software will need to keep up to offer high-resolution output. This will require better algorithms for aligning and mixing images, as well as speedier computing power.
- **Real-time stitching:** At the moment, stitching high-resolution videos can be a laborious procedure. The need for live streaming and event coverage is rising, and real-time stitching would enable it.
- **Automation:** As the need for video material increases, there will be a need for more automated stitching solutions. This can entail automatically detecting and combining video from various cameras using artificial intelligence and machine learning techniques.
- **Mobile integration:** As more people take videos on their smartphones, there will be an increasing need for mobile video stitching solutions. This will require software that is geared for mobile devices and can swiftly handle footage on the go.

Nevertheless, the future of video stitching appears bright, with on-going technological advancements making it simpler to produce stunning panoramic videos in real-time.

References

1) Sharma, Priyanka, and Asha Mishra,"Optimizing Back-Propagation using PSO_Hill_A* and Genetic Algorithm", *International Journal of Computer Applications* **71. 17,** 35-41, (2013).
2) Sharma, Priyanka, and Asha Mishra. "Optimizing Back-Propagation using PSO_Hill_A* and Genetic Algorithm." *International Journal of Computer Science and Network Security (IJCSNS)*, **14. 5 ,** 57,(2014).
3) Sharma, Priyanka, and Asha Mishra,"Optimizing Back-Propagation using PSO_Hill and PSO_A", *Int. J. of Scientific and Research Publications*, (2013).
4) Chau, Harrison, and Robert Karol. "Robust panoramic image stitching." *Department of Aeronautics and Astronautics Stanford University Stanford*, CA, USA (2014).
5) Levin, Anat, Assaf Zomet, Shmuel Peleg, and Yair Weiss. "Seamless image stitching in the gradient domain." *In Computer Vision ECCV 2004: 8th European Conference on Computer Vision, Prague, Czech Republic, May 11-14, ,Proceedings*, Part **IV 8**, pp. 377- 389. Springer Berlin Heidelberg, (2004).
6) Adel, Ebtsam, Mohammed Elmogy, and Hazem Elbakry. "Image stitching based on feature extraction techniques: a survey." *International Journal of Computer Applications* **99, no. 6** (2014): 1-8.
7) Wei, L. Y. U., Zhou Zhong, Chen Lang, and Z. H. O. U. Yi. "A survey on image and video stitching." *Virtual Reality & Intelligent Hardware* **1, no. 1** (2019): 55-83.
8) Bakar, Siddique Abu, Xiaoming Jiang, Xiangfu Gui, Guoquan Li, and Zhangyong Li. "Image stitching for chest digital radiography using the SIFT and SURF feature extraction by RANSAC algorithm." *In Journal of Physics: Conference Series*, **vol. 1624, no. 4,** p. 042023. IOP Publishing, (2020).
9) Lin, Kaimo, Nianjuan Jiang, Loong-Fah Cheong, Minh Do, and Jiangbo Lu. "Seagull: Seam-guided local alignment for parallax tolerant image stitching." *In Computer Vision– ECCV 2016: 14th European Conference, Amsterdam, The Netherlands,*

October 11-14, 2016, Proceedings, **Part III 14**, pp. 370-385. Springer International Publishing, (2016).
10) Jiang, Wei, and Jinwei Gu. "Video stitching with spatial-temporal content-preserving warping." *In Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pp. 42-48. (2015).
11) Zaragoza, Julio, Tat-Jun Chin, Michael S. Brown, and David Suter. "As-projective-aspossible image stitching with moving DLT." *In Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2339-2346. (2013).
12) Zhang, Fan, and Feng Liu. "Parallax-tolerant image stitching." *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3262-3269. (2014).
13) Chen, Chia-Yen, and Reinhard Klette. "Image stitching—comparisons and new techniques." *In Computer Analysis of Images and Patterns: 8th International Conference, CAIP'99 Ljubljana, Slovenia, September 1–3, 1999 Proceedings* **8**, pp. 615-622. Springer Berlin Heidelberg, (1999).
14) Lai, Wei-Sheng, Orazio Gallo, Jinwei Gu, Deqing Sun, Ming-Hsuan Yang, and Jan Kautz. "Video stitching for linear camera arrays." *arXiv preprint arXiv:***1907.13622** (2019).
15) Oyallon, Edouard, and Julien Rabin. "An analysis of the SURF method**." ,Image Processing On Line 5** (2015): 176-218.
16) Peleg S, Rousso B, Rav-Acha A, Zomet."A Mosaicing on adaptive manifolds". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **22 (10)** (2000), pp. 1144-1154,DOI: 10.1109/34.879794
17) He B, Yu S." Parallax-Robust Surveillance Video Stitching", *Sensors*, **16(1)** (2016), p. 7 DOI: 10.3390/sl6010007
18) Uyttendaele M, Eden A, Skeliski R. "Eliminating ghosting and exposure artifacts in image mosaics". *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Kauai, HI, USA* (2001), p. II
19) Nie Y, Su T, Zhang Z, Sun H, Li G." Dynamic Video Stitching via Shakiness Removing". *IEEE Transactions on Image Processing*, **27 (1)** (2018), pp. 164-178 DOI: 10.1109/TIP.2017.2736603
20) Su T, Nie Y, Zhang Z, Sun H, Li G. "Video stitching for hand-held inputs via combined video stabilization". *SIGGRAPH ASIA 2016 Technical Briefs, Macao, China* (2016), p. 25
21) Lin K, Liu S, Cheong L F, Zeng B."Seamless video stitching from hand-held camera inputs", *Computer Graphics Forum*, **35 (2)** (2016), pp. 479-487 DOI: 10.1111/cgf.l2848
22) Zhi Q, Cooperstock J R." Toward dynamic image mosaic generation with robustness to parallax" *IEEE Transactions on Image Processing***, 21 (1)** (2012), pp. 366-378
23) Liu, W X, Chin T J. "Correspondence Insertion for As-Projective-As-Possible Image Stitching". 2016
24) Chang C H, Sato Y, Chuang Y." Shape-preserving half-projective warps for image stitching ".*Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA* (2014), pp. 3254-3261
25) Li N, Xu Y, Wang C." Quasi-homography warps in image stitching". *IEEE Transactions on Multimedia*, **20(6)** (2018), pp.1365-1375 DOI: 10.1109/TMM.2017.2771566
26) Herrmann C, Wang C, Bowen R S, Keyder E, Zabih R." Object-Centered Image Stitching Computer Vision – ECCV". *Springer International Publishing* (2018), pp. 846-861
27) Guo H, Liu S, He T, Zhu S, Zeng B, Gabbouj M." Joint Video Stitching and Stabilization From Moving Cameras". *IEEE Transactions on Image Processing*, **25 (11)** (2016), pp. 5491 5503 DOI: 10.1109/TIP.2016.2607419
28) Li N, Xu Y, Wang C. "Quasi-homography warps in image stitching". *IEEE Transactions on Multimedia*, 2018, **20(6):** 1365–1375DOI:10.1109/TMM.2017.277156
29) Zhang F, Liu F. "Parallax-tolerant image stitching". *In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Columbus, OH, USA*, 2014, 3262–3269
30) Chen Y S, Chuang Y. "Natural Image Stitching with the Global Similarity Prior Computer Vision – ECCV 2016", *Springer International Publishing*, Cham (2016), pp. 186-201 DOI: 10.1007/978-3-319-46454-1_12
31) Zhang G, He Y, Chen W, Jia J, Bao H."Multi-Viewpoint Panorama Construction with Wide-Baseline Images." *IEEE Transactions on Image Processing*, **25 (7)** (2016), pp. 3099-3111 DOI: 10.1109/TIP.2016.2535225
32) Xiang T Z, Xia G S, Bai X, Zhang L." Image stitching by line-guided local warping with global similarity constraint", *Pattern Recognition*, **83** (2018), pp. 481-497 DOI: 10.1016/j.patcog.2018.06.013
33) Rav-Acha A, Pritch Y, Lischinski D, Peleg S."Dynamosaics: video mosaics with non-chronological time". *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, CA, USA* (2005), pp. 58-65
34) Nie, Lang, Chunyu Lin, Kang Liao, Shuaicheng Liu, and Yao Zhao. "Unsupervised deep image stitching: Reconstructing stitched features to images." *IEEE Transactions on Image Processing 30* (2021): 6184-6197.
35) Lai, Wei-Sheng, Orazio Gallo, Jinwei Gu, Deqing Sun, Ming-Hsuan Yang, and Jan Kautz. "Video

stitching for linear camera arrays." arXiv preprint arXiv:1907.13622 (2019).

36) Prachi Panwar,Prachi Roshan, Rajat Singh, Monika Rai1, Asha Rani Mishra and Sansar Singh Chauhan," DDNet- A Deep Learning Approach to Detect Driver Distraction and Drowsiness," *Evergreen*.**9(3)**, 881-892 (2022) doi.org:10.5109/4843120
37) Chaudhary, Hemant Kumar, Kartikeya Saraswat, Harshita Yadav, Hrithik Puri, Asha Rani Mishra, and Sansar Singh Chauhan. "A Real Time Dynamic Approach for Management of Vehicle Generated Traffic." Evergreen. **10(1),** 289-299 (2023). doi.org/10.5109/67 81078
38) Yussupov, Alibek, and Raya Z. Suleimenova. "Use of Remote Sensing Data for Environmental Monitoring of Desertification." *Evergreen.* **10(1),** 300-307 (2023). doi.org/10.5109/6781082
39) P. Tungjiratthitikan, "Accidents in thai industry between 2001 and 2017," *Evergreen*. **5(2),** 86-92, (2018), doi.org:10.5109/1936221
40) Dief, Tarek N and Yoshida Shigeo, "System Identification for Quad-rotor Parameters Using Neural Network", *Evergreen.* **3(1)**, 6-11, (2016), doi.org:10.5109/1657380.
41) Patil, Lalit N., and Hrishikesh P. Khairnar,"Investigation of human safety based on pedestrian perceptions associated to silent nature of electric vehicle", *Evergreen.* **8*(2)***, 280-289 (2021) doi.org:10.5109/4480704