



# A Survey On Image Stitching Using Machine Learning

Gayatri rule<sup>1</sup>, Prof. Manisha Desai<sup>2</sup>, Hadish Mohammed<sup>3</sup>, Harsh Deore<sup>4</sup>, Sumedh Bhosale<sup>5</sup>

<sup>1</sup>B.E 4<sup>th</sup> year, <sup>2</sup>Professor, <sup>3</sup>B.E 4<sup>th</sup> year, <sup>4</sup>B.E 4<sup>th</sup> year,  
Department of Computer Engineering,  
RMDSSOE, Pune-411058, India

**Abstract** : Image stitching is a fundamental computer vision task that involves combining multiple overlapping images into a seamless panorama. This paper presents an innovative approach that integrates machine learning techniques with the speeded up robust features (SURF) algorithm to achieve robust and accurate image stitching. SURF is employed for key point detection and feature matching, while machine learning models enhance the process by improving key point selection, outlier rejection, and fine-tuning image alignment. The combination of SIFT and machine learning yields superior results, making it an efficient solution for creating high-quality panoramic images and enhancing the robustness of image stitching in various applications, such as augmented reality and satellite imagery processing.

## I. INTRODUCTION

The problem addressed is the need to seamlessly combine multiple images to create panoramic views. Conventional single images have limitations in capturing vast or detailed scenes. The challenge is to efficiently and accurately align and blend these images using the Speeded-Up Robust Features (SURF) algorithm, enabling the creation of visually coherent and extended panoramas for various applications, from photography to visual analysis and virtual reality [1].

A machine learning project involves using algorithms and data to train models that can learn patterns and make predictions autonomously. It begins with defining a problem and collecting relevant data, which is then preprocessed for model training. The choice of a suitable algorithm, model training, and tuning its settings follow. Evaluating the model's performance and deploying it into real-world scenarios completes the project, which often spans domains like image recognition, predictions, or natural language understanding. These projects aim to automate tasks and derive insights from data that might be complex or impossible to program explicitly.

Image stitching using the Speeded-Up Robust Features (SURF) algorithm entails keypoint detection, descriptor computation, point matching, image alignment via geometric transformations, and seamless blending. This amalgamation of techniques facilitates the creation of a panoramic view by identifying salient features, aligning images, and integrating them coherently.

Image stitching is a computational technique used to combine multiple overlapping images into a single, seamless panoramic or wide-angle image. It involves a series of steps that aim to align and blend the individual images to create a cohesive and visually pleasing result.

The process begins by identifying common features or points of interest in the images. These features serve as reference points for aligning the images correctly. Various algorithms, such as feature detection and matching techniques, are employed to identify and match corresponding features across the images.

Once the images are aligned, the next step is to blend them together. This involves reducing or eliminating visible seams or discontinuities between adjacent images. Various blending methods, such as gradient-based blending or feathering, are applied to achieve a smooth transition between the images.

To ensure high-quality results, additional steps may be taken, such as exposure compensation, color correction, and perspective correction, to enhance the overall visual coherence of the stitched image.

Image stitching finds applications in a wide range of fields, including photography, virtual reality, surveillance, cartography, and medical imaging. It enables the creation of panoramic photographs, immersive virtual tours, and large-scale visualizations that provide a broader perspective and richer detail than what a single image can capture.

### Index : Image processing , Feature detection , Warping estimation

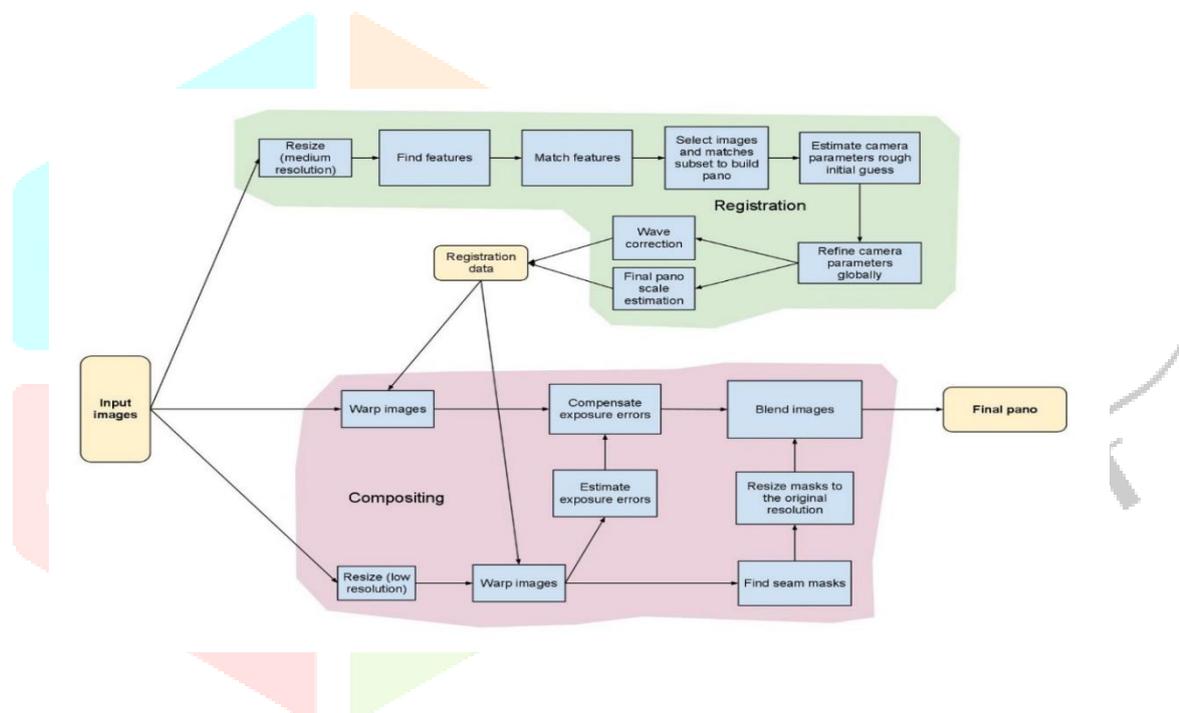


Figure 1: The stitching module pipeline implemented in the Stitcher class [2]

## II. RELATED WORK

In this section, we review prior research relevant to our proposed system. We categorize related work into several key areas that have a direct bearing on our research.

### 1. “Farmland Aerial Images Fast-Stitching Method and Application Based on Improved SIFT Algorithm”

The main black land conservation measure in China is the straw return to the fields. [3] The processing of high-resolution images collected by aerial photography of UAVs through image stitching technology can provide image information for achieving fast and accurate detection of straw cover over large areas. The classical SIFT algorithm has many drawbacks, such as high dimensionality of feature descriptors, high computational effort, and low matching efficiency. To solve the problems above, this study proposes an improved algorithm. First, the method down sampled the high-resolution images before detecting the features to reduce the number of feature points and improve the efficiency of feature detection

## 2. “Deep Rectangling for Image Stitching: A Learning Baseline”

Stitched images provide a wide field-of-view (FOV) but suffer from unpleasant irregular boundaries. [4] To deal with this problem, existing image rectangling methods devote to searching an initial mesh and optimizing a target mesh to form the mesh deformation in two stages. Then rectangular images can be generated by warping stitched images. However, these solutions only work for images with rich linear structures, leading to noticeable distortions for portraits and landscapes with non-linear objects. In this paper, we address these issues by proposing the first deep learning solution to image Rectangling. Concretely, we predefine a rigid target mesh and only estimate an initial mesh to form the mesh deformation, contributing to a compact one-stage solution. The initial mesh is predicted using a fully convolutional network with a residual progressive regression strategy. To obtain results with high content fidelity, a comprehensive objective function is proposed to simultaneously encourage the boundary rectangular, mesh shape-preserving, and content perceptually natural. Besides, we build the first image stitching rectangling dataset with a large diversity in irregular boundaries and scenes. Experiments demonstrate our superiority over traditional methods both quantitatively and qualitatively..

## 3. “HMIML: Hierarchical Multi-Instance Multi-Label Learning of Drosophila Embryogenesis Images Using Convolutional Neural Networks”

The Drosophila embryonic gene expression images provide important spatiotemporal expression information for understanding the mechanisms of Drosophila embryogenesis. [5] Automatic annotation of these images is an imperative but challenging task. Unlike the auto-annotation for nature images, the labels (terms from a controlled vocabulary) are assigned to genes rather than images. Each gene corresponds to a set of images, and different genes are associated with different numbers of images and labels, thus conventional machine learning methods are not applicable in such a scenario. In this study, we treat this task as a multi-instance multi-label (MIML) problem, and propose a hierarchical MIML learning framework, called HMIML. We implement HMIML at image-level and gene-level, respectively, both using convolutional neural networks. Especially, an image stitching strategy is employed to get a combined image representation at gene-level. Experimental results on the Fly Express database show that HMIML enhances annotation accuracy on all developmental stages compared with the existing methods. Index Terms—gene expression, Drosophila embryonic image, multi-instance multi-label learning, convolutional neural network.

## 4. “Automatic Image Stitching Using SIFT”

This paper concerns the problem of automatic image stitching which mainly applies to the image sequence even those including noise images [6]. And it uses a method based on invariant features to realize fully automatic image stitching, in which it includes two main parts: image matching and image blending. As the noise images have large differences between the other images, when using SIFT features to realize correct and robust matching, it supplies a probabilistic model to verify the panorama image sequence. In addition to have a more satisfied panorama image, it uses a simple and fast blending method which is weighted average method. Finally, the experimental results confirm the feasibility of our methods.

## 5. “Robust Panoramic Image Stitching”

Creation of panoramas using computer vision is not a new idea, however, most algorithms are focused on creating a panorama using all of the images in a directory. [7] The method which will be explained in detail takes this approach one step further by not requiring the images in each panorama be separated out manually. Instead, it clusters a set of pictures into separate panoramas based on scale invariant feature matching. Then uses these separate clusters to stitch together panoramic images. The method which will be explained in detail takes this approach one step further by not requiring the images in each panorama be separated out manually.

## 6. "Content-dependency reduction with multi-task learning in blind stitched panoramic image quality assessment"

In this work, we investigate deep learning based solutions to blind quality assessment of stitched panoramic images (SPI) [8]. The main problem to tackle is that the ground truth data is usually insufficient. As a result, the learned model can easily overfit data with specific content. Because most distortions of SPIs lie within local regions, the problem cannot be alleviated by commonly-used patch-wise training, which assumes local quality equals global quality. We propose a multi-task learning strategy which encourages learned representation to be less dependent on image content. A network with two weight-shared CNN branches is trained to simultaneously compare the quality of two images of the same scene and predict the quality score of each image. Since two images of the same scene are processed by the same CNN, the CNN tends to find their quality differences instead of content differences under the constraint of the quality ranking objective. Because two tasks share the same representations learned by the CNN, the regression task can be further benefited from the quality sensitive representations. Extensive experiments demonstrate the effectiveness of the proposed model and its superiority over existing SPI quality assessment methods.

## 7. "A Review of Image Mosaicing Techniques"

Image Mosaicing technology is becoming more and more popular in the fields of image processing, computer graphics, computer vision and multimedia. It is widely used in daily life by stitching pictures into panoramas or a large picture which can display the whole scenes vividly. For example, it can be used in virtual travel on the internet, building virtual environments in games and processing personal pictures. Image Mosaicing is firstly divided into (usually equal sized) rectangular sections, each of which is replaced with another photograph that matches the target photo. When viewed at low magnifications, the individual pixels appear as the primary image, while close examination reveals that the image is in fact made up of many hundreds or thousands of smaller images. This paper primarily focuses on addressing the challenges involved in creating high-resolution image mosaics or panoramas. It introduces a comprehensive approach that involves two critical aspects: Accurate registration and Robust Blending. The significance of this work lies in its emphasis on both accurate registration and robust blending techniques, essential pillars for creating high-quality panoramic images. By addressing these aspects, the paper contributes to improving the visual quality and fidelity of stitched panoramas, which is crucial for various applications, including photography, cartography, virtual reality, and more [9].

## 8. " Parallel Algorithms for Motion Panorama Construction":

The research paper on " Parallel Algorithm for Motion Panorama Construction" likely focuses on optimizing the computational process involved in creating panoramic images by leveraging parallel processing techniques. [10]

This research delves into enhancing the speed and efficiency of creating panoramic images by utilizing parallel processing methods. Traditional methods for stitching multiple images to form panoramas can be computationally intensive and time-consuming. This paper explores how to divide the stitching process into smaller, parallelizable tasks that can be processed concurrently. By harnessing the power of parallel computing, such as utilizing multi-core processors or distributed computing environments, the stitching process can be significantly accelerated. The focus is on optimizing the stitching algorithm's implementation to leverage parallelism effectively, resulting in faster and more efficient panorama construction.

## 9. " Image Stitching Algorithm for Drones Based on SURF-GHT "

This hypothetical paper likely discusses how employing the SURF [11] algorithm within robotic systems can aid in creating panoramic images or stitched views, potentially benefiting applications like robot navigation, mapping, or surveillance where comprehensive visual information is crucial. It might also delve into optimizations or adaptations of the SURF algorithm to suit the constraints or requirements of robotic platforms in terms of computational efficiency and real-time processing.

### 10. "SURF based matching for SAR image registration"

This hypothetical paper likely delves into techniques and strategies to accelerate the [12] SURF algorithm's feature matching capabilities to meet the demands of real-time applications. It might discuss optimizations, parallelization, or hardware acceleration techniques that enable the algorithm to process image features swiftly while maintaining accuracy, making it relevant for real-time computer vision tasks such as object tracking, augmented reality, or video analysis.

### III. CONCLUSION

In conclusion, the SURF algorithm's speed, robustness to scale and rotation, and efficient feature matching make it a valuable choice for image stitching applications, particularly in scenarios where real-time performance and accuracy in feature matching are crucial. However, it's essential to consider its limitations and potential integration with complementary techniques for improved performance in challenging conditions.

### References

- [1] "https://en.wikipedia.org/wiki/Image\_stitching," Wikipedia . [Online].
- [2] A. Rosebrock, "pyimagesearch," 17 December 2018. [Online]. Available: [https://pyimagesearch.com/wp-content/uploads/2018/12/image\\_stitching\\_opencv\\_pipeline.png](https://pyimagesearch.com/wp-content/uploads/2018/12/image_stitching_opencv_pipeline.png).
- [3] M. H. Y. W. ., Y. S. ., A. X. G. YUANYUAN LIU, "Farmland Aerial Images Fast-Stitching Method and Application Based on Improved SIFT Algorithm," *IEEE*, 2022.
- [4] C. L. K. L. S. L. Y. Z. Lang Nie, "Deep Rectangling for Image Stitching: A Learning Baseline," *arXiv*, 2022.
- [5] T. Li, Y. Yang and H.-B. Shen, "HMIML: Hierarchical Multi-Instance Multi-Label Learning of Drosophila Embryogenesis Images Using Convolutional Neural Networks", " *IEEE*, 2018.
- [6] Y. W. W. H. Z. Z. Lanfang Li, "Automatic Image Stitching Using SIFT," *IEEE*, pp. 5-10, 2008.
- [7] R. K. Harrison Chau, "Robust Panoramic Image Stitching," *Stanford University*, 2015.
- [8] W. L. a. B. Z. Jingwen Hou, "'Content-dependency reduction with multi-task learning in blind stitched panoramic image quality assessment", " *Research gate* , Oct 2020.
- [9] P. K. N. Dushyant Vaghela, "A Review of Image Mosaicing Techniques," *arXiv*, 2014.
- [10] S. B. Yong Wei, "Parallel Algorithms for Motion Panorama Construction," *2006 International Conference on Parallel Processing Workshops (ICPP Workshops 2006), 14-18 August 2006, Columbus, Ohio, USA*, Jan 2006.
- [11] Y. L. ., H. ., Z. W. a. H. Z. Haohua Duan, "Image Stitching Algorithm for Drones Based on," *IOP Conf. Series: Materials Science and Engineering 569 (2019) 052025*, 2019.
- [12] D.-S. P. ., U. C. P. Ujwal kumar durgam, "SURF based matching for SAR image registration," *Conference: 2016 IEEE Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, 2016.