Stitch Multiple Images for Generating Quality Panorama

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Copyright Statement

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Abstract

Key Words: *Panorama, stitching, blending, ghosting, Artifacts, seamless*

Stitching multiple images for achieving the 360 view of any environment is a challenging task. Traditionally, the whole process of image stitching is based on distinctive features that are very helpful for estimating the other parameters of the whole algorithm. As different images require different suitable parameters or weights for achieving the best results and we need to predict those suitable parameters for each case independently. In our proposed model first small neural network based techniques are implemented that are just used for estimating the quality panorama hyper parameters and then we apply the whole stitching algorithm on sample images by using those predicted parameters.

Therefore, due to lack of labeled data we are unable to train any supervised model for those hyper parameter selection that’s why we build an unsupervised technique that makes decisions based on just extracted features quality, confidence and count of inliers etc.

By estimating the good parameters we are able to stitch a quality panorama that doesn't have any ghosting artifacts, blending discontinuities, seamless and alignment errors as well. We evaluate the performance of our proposed model on three datasets and analyze performance in both perspective quality and computational time and conclude that our model outperforms with other state of the art stitching algorithms in both perspectives.

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CHAPTER 1
INTRODUCTION

Image stitching is a technique that is used for combining multiple images with overlapping areas to produce a wide angle view that is called panorama.

Designing an algorithm that extracts useful features and does standard stitching is a decisive and critical problem of many computer vision tasks such as visual localization, simultaneous localization and mapping (SLAM) and structure from motion (SFM). The whole technique of image stitching is mainly based on detected features that define the characteristic of the object and further use for searching the similar object and those features must be independent of object position, scale, orientation, illumination and color.

There are two main approaches according to current research that are used for extracting the features: One is hand crafted features that are part of conventional computer vision algorithms and second one is deep learning based approach that uses neural networks for extracting features.

In computer vision the state of the art algorithms are SIFT, SURF, ORB and AKAZE that are used for making a descriptor of each object. The most promising feature extractor algorithm is SIFT, which plays a very important role in feature extraction and matching fields due to their accuracy and distinctiveness[1]

Due to the implausible feature extraction potential of deep learning models almost all fields are trying to move toward convolutional neural networks and achieve incredible accuracy as expected. In image stitching there are multiple steps where we can place deep learning approaches such as for feature extraction, matching, homography estimation, blending, seam finding, warping or etc. In most of the cases only feature extraction parts are replaced with any deep learning based technique due to their complexity and priority in the stitching process and all other steps remain the same as in conventional approaches. Deep learning based techniques directly produce feature descriptors that are most promising w.r.t conventional methods and work well in complicated scenarios with best accuracy[2].

1.1 Motivation and Background

For the time being, for generating the panorama for acquiring the whole 360 view of the environment by using computer vision techniques. This is the most emerging field. Panorama images are very helpful for getting a wide-angle view without using any external resources (360 camera).

A wide angle view of any location can be used in many applications, just like property selling apps, simple mobile applications for public usage, and many more. Stitching the several frames into a panorama creates a wider-angle photo than lenses generally allow. For landscape and architectural photographers mainly, an ultra-ultra-wide perspective is always useful. To get the resolution that comes from stitching frames allows it to make larger, intricate prints as well as have the ability to crop that is used in further post-preprocessing.

The field of computer vision has been growing rapidly and uses different techniques to perform such tasks. These tasks involve reconstruction of the scene, motion analysis, image restoration, and image matching. Image stitching is the technique that uses different images and merges them to get a high-resolution panorama.

For image stitching, different techniques are used some are direct, and others depend on features-based. Direct techniques compare the pixel intensities of the image and reduce the total differences among overlapping pixels[3]. This technique estimates the input of each pixel present in the image and uses the finest content and details of images, but it cannot change the scale and rotation of images. There are some direct methods like optical flow, gradient weighting, locally aligning, graph structure, depth and color.

Features-based techniques get the link between the images based on extracting different features. These methods are high speed and can determine the panorama and accordingly detect the relationship between the images. These features are suitable for automatic panorama stitching. Dual homography, mesh-based, quasi tomography, multi-affine and hypotheses of warping are some of the features-based techniques.

The enlargement in usage of multimedia devices like smartphones and digital cameras, the demand to obtain high quality panoramic images is increasing. Even if image stitching has made huge progress, it is still a challenging process to produce high quality panoramic images that have large parallax and low texture under complex stitching scenes.

Algorithms are used for aligning and stitching images into seamless photo-mosaics. Methods that focus on getting the 2D global transformation to align one image into another, it employs the single global transformation of homography, works under special conditions, and produces results with misalignment and ghosting[3].

Many stitching algorithms like Auto stitch and Photosynth use projective warps, probably for their simplicity, and their success depends on deghosting algorithms to remove unwanted artifacts. So they introduced as-projective-as-possible warps, which not only depend on the projective model and try to fix the resulting error but also give the model based on data to enhance the fitting[4].

1.2 Image stitching

Image stitching is a technique through which we can communicate effectively with the environment just like in virtual reality or 3D view at minimal cost or with less resources. We need our visual tour of the environment with the usages of panorama that has seamless, good quality, immersive, illumination equality and smooth compensation between images. Panorama is basically high resolution images that are created after stitching multiple overlapping regions images and that is how it covers a large field of view of the environment. On the other hand the field of view of the human eye is almost 130*200 and currently available cameras has field 35*50 and that's why we need a list of images of the environment with overlaps for covering large area[5]. For providing the large field of view of the environment there are some other techniques as well, like computer graphics and some digital cameras but the main difference between both of them is the cost and time. Digital cameras are costly and computer graphics techniques need human manual effort.

On the other hand computer vision and deep learning techniques are less costly and we don't require any manual intervention for producing quality results. As deep learning is worth and its usage in current state of the art methods in almost all fields we explore its performance in image stitching.

Image stitching plays an important role in many applications such as for video conferencing, video meeting, and house rental application, visual tour of any location, in medical imagery application, visual localization and video summarization.

1.3 Stitching Process

At first image stitching challenges are solved by using computer vision techniques but with the use of deep learning technology a lot of work related to image stitching algorithms are solved by using deep learning methods. Image stitching is not any end to end technique, it contains sequences of some steps that are also dependent on each other in similar order as they performed.

Main steps are Image calibration, Image registration and Image blending. Those steps are discussed in the following subsection with detail.

1.3.1 Features extraction

Features is the representation of any object, just like embedding's of words for their representation. All different objects contain distinctive features values that define the difference between objects and all similar objects contain features values with minimum distance[6].

In early computer vision many hand crafted filters were used for extracting features from images such as canny edge detection, Sobal, Gaussian and corner detector. All filters are hand crafted and work on gradient change algorithms for just extracting boundaries and corners of objects.

In the development of deep learning, Automatic features filters are selected based on learning weights of the deep learning model, that's how we get more accurate and fast features by using new techniques.

For image stitching, distinctive, fast, accurate, valuable features are most important due to its level of priority. This is the first step of the stitching algorithm and all other steps accuracy and performance are directly dependent on those features accuracy.

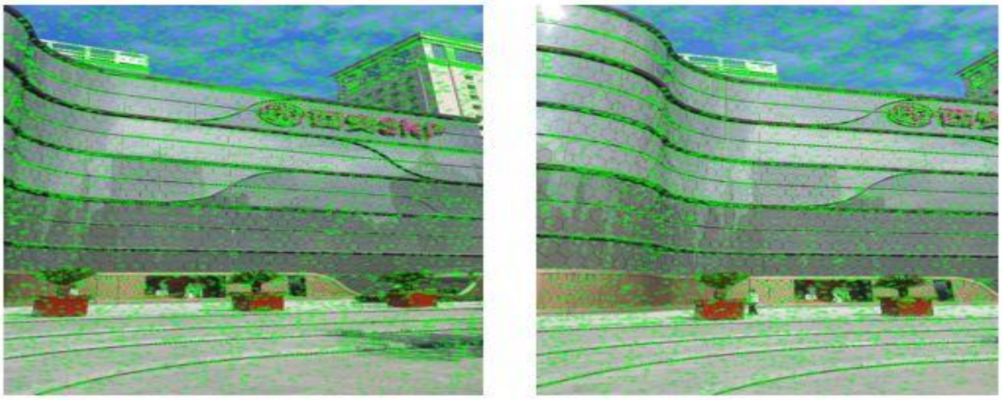

Figure 1: Feature Extraction

In the figure (1), features are extracted from both images and drawn on the input image. We can observe that the edges and corners or something that is important and distinguished are considered as features.

1.3.2 Feature Descriptor

For further processing of features we need descriptors that enhance the accuracy of features by adding neighborhood information. Each feature has some specific location that contains some neighbors, and neighbors are good enough for making them distinctive and valuable. For making a descriptor of features we specified some local boundaries that contribute strongly for gathering information of features. Each descriptor of features must be independent from illumination changes, scale changes, rotation, distortion effects, Exposure artifacts, viewpoint, hardware resource and weather changes as well.

Those descriptors play a very crucial role in image stitching processing, because all other remaining steps are performed based on those calculated descriptors. For further steps we need a descriptor that must be accurate, valuable enough and small size as well. Very large size descriptors increase the complexity for other steps of the algorithm and increase stitching time on a large scale.

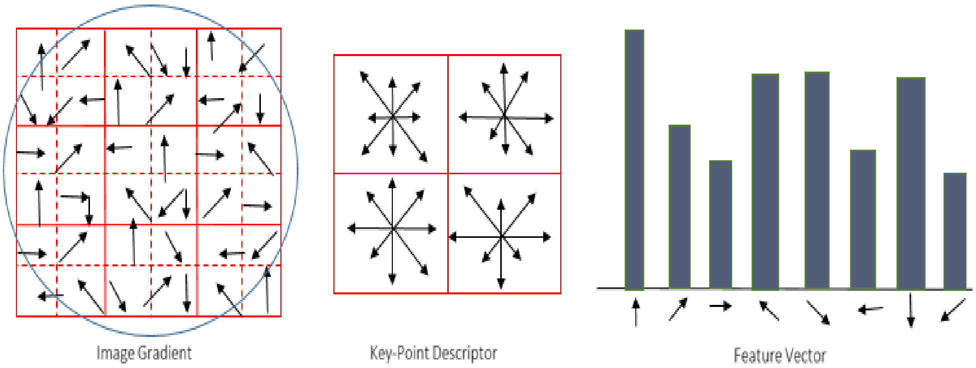

Figure 2: Local Descriptor

As in the figure (2) image, each pixel of image plays a contribution for extracting their neighbor's features descriptor and we calculate the direction of each feature for making them rotation independent based on the highest count of rotation angle.

1.3.3 Homography

Homography is the transformation matrix that is used to combine the place of all images into only one point. We calculate the matrix by using linear regression method and try to achieve the maximum accuracy by decreasing loss function. Large number of points produced good matrix parameters and at least four points are necessary for applying the matrix operations.

All transformation cases are resolved by using this 3*3 matrix, translation, scale, skewness and rotation as well all are handled by using this matrix.

For calibration purposes we must add some other parameters, such as camera focal length and optical center etc. By adding those calibration parameters we have two matrices one is called intrinsic parameters and another one is called extrinsic parameters. After multiplying those two matrices we have one 3*4 matrices named as fundamental matrices[7].

After applying those estimated matrices we are able to transform one image to another image.

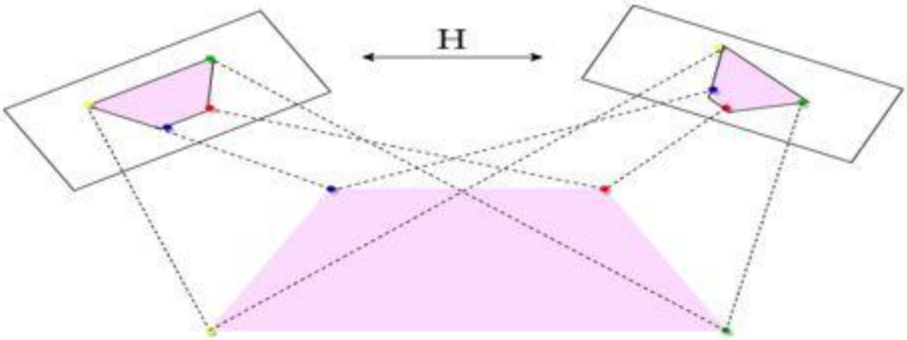

Figure 3: Estimation of Homography Matrix

Here we have two images, one is on the left side and the other one is on the right side, for stitching purposes we need to view them from a single point of view that is achieved by estimating the Homography matrix. This matric place all image into one common place where we can get single panorama.

1.3.4 Multi Homography

As in the case homography is just an estimation of all transformation parameters and trying to achieve a standard scenario for all points of one image is somehow not possible. Only 9 parameters are not enough for estimating transformation of the whole image, that’s why we face ghosting artifacts in most of the cases.

In an outdoor environment, images contain near and far objects and some other complicated objects as well that are not easily stitched by using only one transformation matrix.

That's why multiple homography takes into play and computes multiple homography for transforming only one image to another and the count of homography is dependent on the number of patches in which image is splitted. After estimating multiple homography, ghosting artifacts and outdoor panorama error is seen to be resolved[8].

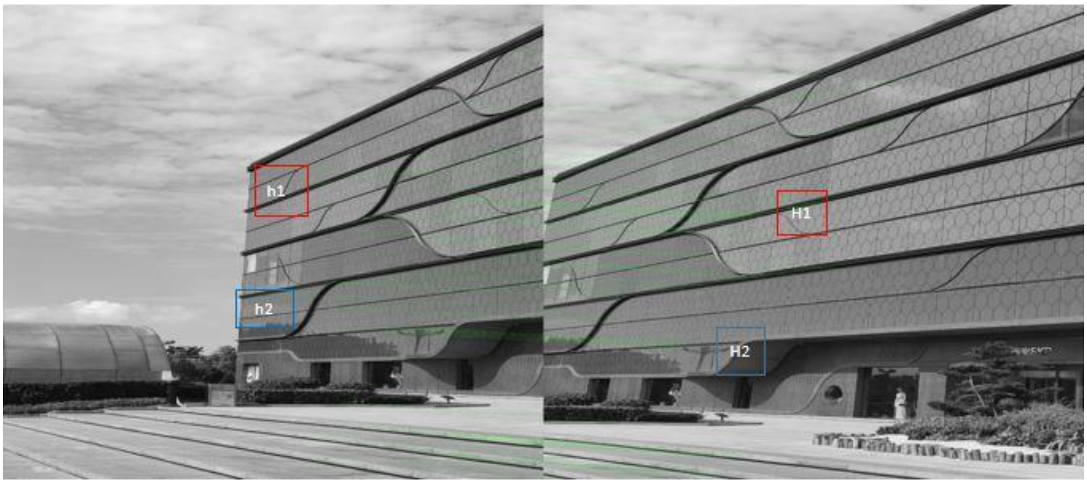

Figure 4: Tow images with Multiple Homographies

As we know it the most challenging problem of image stitching is parallax that is due to our single estimation of homography for the whole image[9]. That is why we calculate multiple homographies on a single image for handling the parallax error.

In figure (4) used for handling upper lines of building we do transformation based on h1 Homography matrix and for handling lower lines of building we do transformation based on h2 Homograpy

1.3.5 Seamless

The homography is just an estimation of all transformation parameters and trying to achieve a standard scenario for all points of one image is somehow not possible. Only 9 parameters are not enough for estimating transformation of the whole image, that's why we face ghosting artifacts in most of the cases.

In an outdoor environment, images contain near and far objects and some other complicated objects as well that are not easily stitched by using only one transformation matrix.

Therefore multiple homography takes into play and computes multiple homography for transforming only one image to another and the count of homography is dependent on the number of patches in which image is splitted. After estimating multiple homography, ghosting artifacts and outdoor panorama error is seen to be resolved.

1.3.6 Blending

Our resultant stitched panorama has many intensities discrepancies that we need to remove for making our results more desirable. For smooth blending to all intensities in the whole panorama, we have a lot of algorithms that apply different hand crafted filters on image and remove prominent lines and unbalanced intensity patches from stitched results. The two main algorithms are taking the edge of visible seams in overlapped region. The one is to blend the entire overlapped region which contains multi-band blending and gradient domain stitching and the other one is to perform images cutting between the images[10].

Traditionally, for blending purposes some smoothing, average, alpha methods are used that perform well in some simple cases but fail in complicated cases. For enhancing the results of blending some deep learning models are trained that estimate weights of learned filters without doing it manually and achieve good results as to previous one. In recent years, some optimal blending techniques are proposed that outperform others and are less complicated as to deep learning techniques.

As all steps of the stitching process are dependent on each other but this one is independent from all previous steps.

1.3.7 Cropping

As our final results contain some black region due to spherical warping and camera distortion effects. Those black regions produce undesirable effects on image and make an unpleasant environment. As black regions contain many ups and downs that we need to handle by using contours detection.

First, we extract contours of stitched panorama and then find the least minimum point in both directions. By using this least minimum point we cut our results and extract a panorama that doesn't have any black region.

1.4 Thesis Aims and Objective

There are two main concerns in this work. First of all, we want stitching that cover whole 360 environment and stitch multiple images in one go with better quality. And the second concern is related to complexity and timing that this process take for achieving this target. We want something that reduce the resources constraint and produce quality work.

The following goals were defined in order to meet the aforementioned problems and demonstrate the working of each stage with proper explanation.

1) Stitch multiple images and make image count independent and image quality independent.
2) Remove ghosting and alignment artifacts without disturbing the resolution quality.
3) Cover whole 360 environment.
4) We want all of the mention capability in our one model with less complexity and less number of resources.
5) To post process the experimental data and obtain the appropriate results.
6) To conduct comparative study of results and obtain appropriate figures in the form of tables, bars, graphs.

1.5 Thesis Outline

Chapter 1: Introduction

This chapter contains brief introduction and overview of problem statement along with the basic scientific concepts of the thesis. The objectives and research outline are also included in this portion

Chapter 2: Literature Review

This chapter includes the past researches in the field of image stitching and feature matching by using deep learning and computer vision techniques.

Chapter 3: Methodology

This chapter contains the detail of all process that we were proposed and whole procedure from start to end for obtaining fortunate results.

Chapter 4: Results & Discussions

This chapter includes the individual outcomes as well as the comparison with other state of the results in form of visual panorama images and time table that it will take for processing.

Chapter 5: Conclusions

This chapter contains a summary of the thesis and highlights the overall outcomes in a brief manner.

Chapter 6: Future Recommendations

This chapter includes the future scope of the study and research gap for upcoming authors and researchers.

Chapter 7: References

This chapter contains the articles, conference papers and research paper's trajectory, which are referenced in this study.

CHAPTER 2

LITERATURE REVIEW

In the section we shortly review the traditional image stitching methods and deep images stitching methods.

The main objective of this work is to handle illumination problems during stitching and make it independent of efficient descriptors. For this target they use a deep learning based technique called IF-Net and predict features descriptors of size 128 with the replacement of SIFT(Statistical approach)[11].

The main intention of the model is to enhance the performance of the composition part of the stitching pipeline and they build an end to end pipeline for achieving this task. Their proposed model has two branches, one is for composition purposes and second one is for perceptual edges. Edge branch helps during prediction of blending weights and stitch image is weighted sum of this blending weights with input image[12]

For transformation purposes they estimate multiple homographies rather than one and also introduced MRF energy function with confidence term, duplicate term and smoothness term for handling multiple homography[13].

GANs based network to remove parallax from the generated panorama. They trained models on self-made dataset and achieved quality accuracy[14].Use a deep learning model for estimating the transformation matrix called homography. Their network follows supervised learning procedures and is trained on constructed datasets[15].

They treat one image stitching problem as multiple patches stitching problem by dividing the image into multiple patches. That's how they need multiple homographies corresponding to each patch and warped them by applying homography transformation on each pixel based on its respective patch. By doing this approach they handle the most challenging parallax error in image stitching in an accurate manner[16].

Find local homographies for overlapping regions and linearize homographies for non-overlapping regions for removing the projective distortion. Also introduced local similarity measure for estimating the motion of the camera rather than global similarity measure[17].

Generate multiple homography, displacement maps and weights maps at the same time by using only one proposed network for removing the parallax distortion on the created dataset. Proposed network are end to end models that train on appearance matching loss and depth layer loss[18].

Two convolutional neural networks are trained, first one is a regression model that estimates the parameters of homography and second one is classification network that is used for distribution of quantized homography. Model estimates the four corners of input images without any separate features extraction and descriptor estimation[7].

Proposed that single perceptive warping can be done by parametric warping that combines the APAP and quasi-homography via dual features and mesh based warping which optimize the energy function including alignment, naturalness, distortion and saliency[19].

Extracted the line and edge features from stitched images and added the energy term to the GSP model and weights to sampling points to get a smooth transition between local alignment and geometric structure preservation[20].

Introduced the global collinear structure into object function which maintains the local and global structures during the alleviating distortion. The result is 31% lower than the SPW by using average RMSE for point matching[21].

Highlight the image blending based algorithm using asymmetric bidirectional optical flow which produces the high quality 360-degree spherical panoramic image. It also uses the graphics processing unit to reduce the processing time so it takes less than 30s to stitch the 9000-by-4000 pixel image[22].This is an end to end model for image stitching and contains two parts one for transformation purpose and other for reconstruction. Do image stitching on images that have less features and low resolution. [23].

Model is capable for stitching images that have large variations in depth, color and texture as well. They proposed an energy function especially for structure distortion and enhance the invisibility of seam in resultant image. Energy function contain one additional depth term that help the model for enhancing smoothing seam estimation[24].

Stitch images contain some irregular boundaries that may be reduced by selecting an initial mesh and estimate the target mesh according to this but this solution does work only on highly structured and clear images. For improving the performance on less structure and less quality images they design a deep learning model. This model is an end-to-end pipeline with predefined fixed mesh for only finding the initial mesh by using deformation method.

For achieving good results a comprehensive objective function is build that is also used for preserving the boundaries of predicted mesh[25].

Propose a method that works with fixed camera position and projection methods that are hierarchical by using depth information of images. This method removes the dependency of feature points because sometimes in complicated cases feature points contain some outliers. That's how the complexity of features extraction, feature descriptor and outlier scenario are removed and we restrict captured hardware[26].

Propose a methodology that has two modules one is multi scale deep homography estimation and second one is edge preserving deformation estimation. A deep homography matrix is calculated for resolving the transformation errors on sample images and then an edge preserving model is called for estimating the deformation changes between edges to content transformation. Produced results contain high resolution with excellent generalization[27].

Proposed resolution normalizing methods estimate the ground truth sampling distance and accordingly gray value interpolation with GSD allocation are also estimated for stitching the image patch accurately. This normalization helps for stitching complicated images with blending and ghosting antiquity[28].

Use pre trained state of the art network RESNET for extracting features of sample images and then replace them with sift features while all other steps remain the same [29].

For reducing the stitching trace and ghosting errors they propose a novel blending zone that reduces the proposed energy function by adding color, similarity, intensity changes term within overlapping regions. Due to this energy function an optimal seam line is predicted that automatically reduces the ghosting and trace error in resultant panorama [30].

Explained models extract features from images by using traditional computer vision techniques and then apply singular value decomposition on those features for making them fast and work only on important one. Based on geometric relation images are aligned automatically [31].

Build a method that produces quad fisheye panorama by cropping the unwrapped images and then reordering those images for creating a round circle view of resultant images.

Many mesh distortion and rectangular format of results are adopted for enhancing the accuracy of the model. They further improve their stitching algorithm and then evaluate it on a video dataset that also outperform with other comparable model [32]

CHAPTER 3
METHODOLOGY

3.1 Sequence of Procedure

Our methodology contains different steps that are implemented in sequential manners because they are dependent on each other and process one after the other. First step of our proposed method is parameter estimation that needs to be calculated at starting before doing anything related to stitching. Those predicted parameters are useful in further steps and predefine our optimal path and help for taking decisions during feature extraction and making confidence selection. Those two decisions play a very important role for stitching and produce best possible results that are achievable. After that we calculate features that contain locally dependency and scaling independency. By using data from those feature descriptors we apply simple linear regression techniques and estimate all transformation parameters. At the end those predicted transformation parameters help to place corners of each image into one common place. All remaining steps are just applied for enhancing the visualization and quality of resultant panorama such as compensator, seam extraction and cropping.

There are multiple parameters that are used for calculating homography, sometimes we need different types of features and sometimes we need to go with low confidence of matching points for calculating the homography and in most of the cases high confidence matching points produce the most promising results by calculating homography.

Those selection parameters are totally dependent on input images and change according to the situation of results. For predicting the most promising hyper parameters for each input sample we design a small neural network that is able to predict the optimal features extraction model with their suitable parameters and matching confidence as well based on the relation and quality between inputs samples.

This is how we have optimal parameters for each sample and based on this we perform a stitching process that produces optimal possible results.

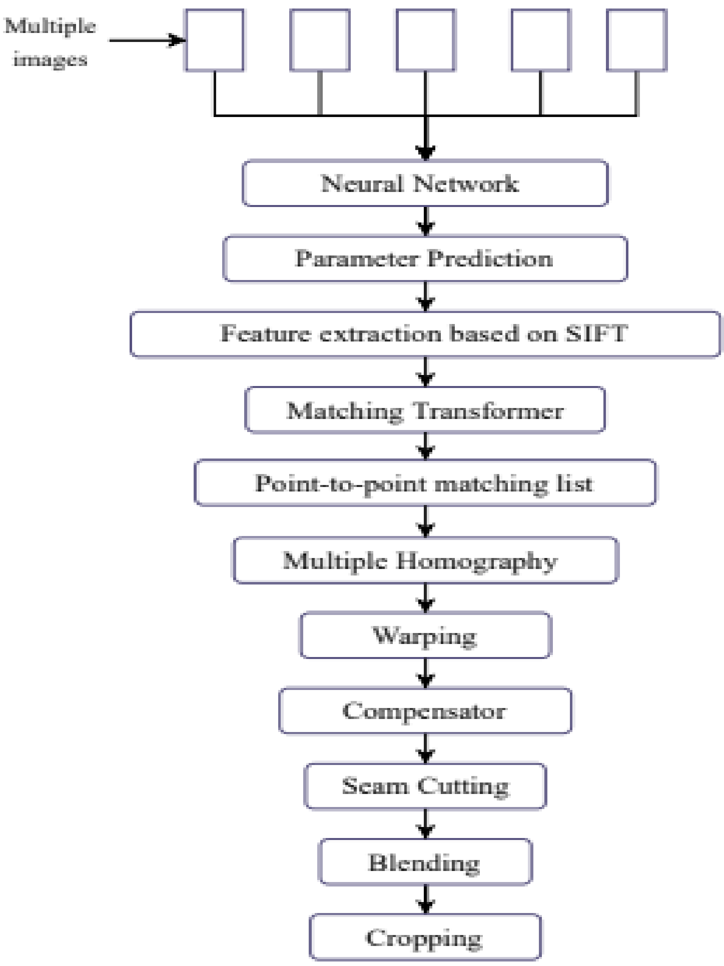

Figure 5: Flow chart of image stitching

In the created flow chart we mention steps of our model that are done in sequential manners one after the other due to their dependency.

3.2 Feature Extraction

For extracting features first we scale down the image into multiple steps and then calculate the difference of Gaussian between those scaled images. We do scaling to make our features scale independent and make them more robust in different situations. For enhancing rotation independence we calculate feature rotation by taking neighbors dimension information and this is how we are able to introduce feature rotation/dimension independence in our algorithm.

Only features of objects are not enough for matching the similar object in another environment because there are multiple environments that take place of this type of similar object. Our algorithms must be efficient to identify the object that also contains a similar environment and have a large amount of evidence for validating the similarity of the object. Our extracted features must be object dependent and locally dependent on neighbor features as well.

For introducing this capability in our algorithm we create a descriptor for each feature, this descriptor combines useful information from neighbor features that make them stronger and locally dependent. At the end our algorithm takes input as an image and returns key points with a detailed descriptor. The size of key points are totally dependent on the number of features that are extracted by algorithm, such as plane environments contain less features as to object oriented environment, Objects corners, height, lines play a more important role in features extraction as compared to wall and plane objects. The size of the descriptor is similar to features but with more depth because it contains neighbor information as well. With the help of descriptors our feature worth increases and basically we embed both scale/dimension independence and locally dependence on our algorithm for achieving best results.

$$I = Is1 + Is2 + Is3 \ldots\ldots..Isn \qquad n \in scale \tag{1}$$

$$S1 = n \times n\ ,\ S2 = \frac{n}{2} \times \frac{n}{2}\ ,\ S3 = \frac{n}{4} \times \frac{n}{4} \ldots\ldots\ldots.\ Sn = \frac{n}{Sn} \times \frac{n}{S} \tag{2}$$

$$Gs1\ = G(Is1x, Is2y, k5) \tag{3}$$

$$I = Gs1, Gs2, Gs3, \ldots\ldots\ldots..Gsn \tag{4}$$

$$Gs2 - Gs1 = Gs21, Gs3 - Gs2 = Gs32, \ldots\ldots\ldots\ldots.Gn - Gn - 1 = Gn(n-1) \tag{5}$$

$$mag = M(Gs21, Gs32, \ldots\ldots\ldots\ldots G(n-1)n) \tag{6}$$

$$ang = \ \tan -1\,(\frac{Gs21}{Gs32}) \tag{7}$$

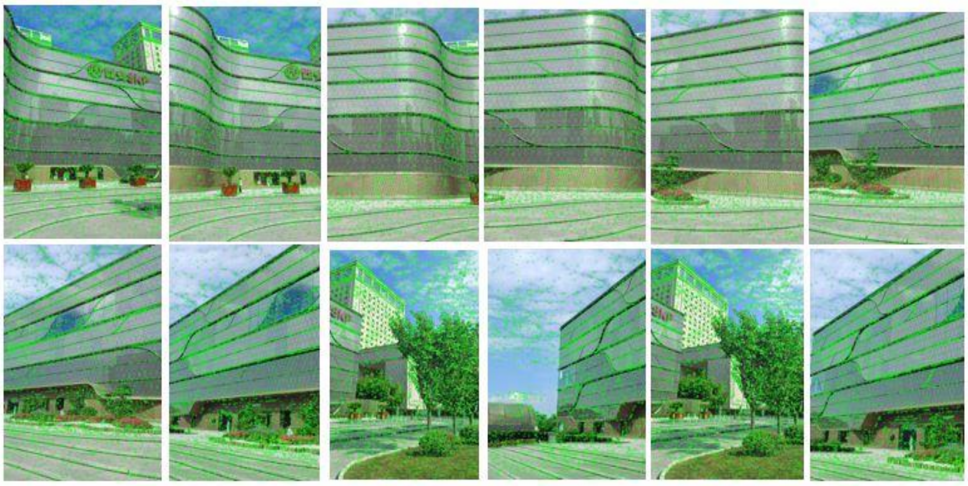

Figure 6: Feature Extraction of multi images

We perform a stitching process on one sample image and here we visualize the extracted features based on optimal parameters. Features of all sample images are not dependent on each other that's why we can calculate those features in parallel manners rather than in sequence.

3.3 Homography Estimation

As for stitching purposes we need to attach images based on their similarity portion, for achieving this target we need to place all images into one common plane and find the position of each image by taking just their top left corner.

For transforming all images of sample data into one common plane we need to calculate a transformation matrix that covers all possible transformation aspects such as rotation, scaling, shifting, skewness, camera position, camera focal length.

This transformation of all images is not possible in a 2D environment because we have camera parameters as well that take place in the 3D world.

This estimated matrix is usually called a fundamental matrix that is an abstraction of two other matrices, one is extrinsic and other one is intrinsic. Extrinsic matrices are the estimation of rotation difference, scaling difference and all others possible transformation between images. This estimation is done by using a simple linear regression model that tries to find the best fit line between input and output points.

$$\begin{bmatrix} m11, m12, m13, \dots \dots \dots \dots m1n \\ m21, m22, m23, \dots \dots \dots .. m2n \\ \vdots \\ m21, m22, m23, \dots \dots \dots .. m2n \end{bmatrix} \begin{bmatrix} f1 \\ f2 \\ \vdots \\ fn \end{bmatrix} = \begin{bmatrix} m1n \\ m2n \\ \vdots \\ mmn \end{bmatrix} \quad 8$$

$$\begin{bmatrix} f1 & f2 & f3 & f4 \\ f5 & f6 & f7 & f8 \\ f9 & f10 & f11 & f12 \end{bmatrix} = \mathrm{E} \times \mathrm{I} \quad 9$$

$E = TR$ I = Camera Parameter

As is well know we have a descriptor for each extracted features for both images that transformation needs to be estimated, we sort each feature and their corresponding descriptor based on their score and then calculate matching between those sorted features. After finding matches we also apply a sorting algorithm on those matching points based on their matching score.

We also set some threshold for this selection of matching points for ignoring the edge cases and as we discuss above in parameter estimation this parameter is already estimated with our neural network.

As the highest score produces good estimation of the homography matrix and low score produces less confident estimation. At the same time, intrinsic parameters estimation are also done in similar manners as extrinsic estimation are held.

Now we have two matrices that are the decomposition of one fundamental matrix and we achieve this only by multiplying our two estimations.

At the end we have a large plane where all input images are placed and are viewed with a single angle. That's why we transform our all input images to the left corner on this large final plane.

3.4 Ordering of images

Our algorithm creates a large plane and places all input images here, and the order of images process remains the same as pass by user but the position of each image is not in a similar sequence as given.

This sequence is decided by the matching confidence, the pair of images that contain less confident matching scores are placed at corners.

This is how the starting and ending of our resultant panorama are not in similar order as input images.

3.5 Wrapped masks

For removing the stitching and alignment artifacts and the purpose of camera distortion we warp all masks in spherical form and then apply homography on top left corners of all images. There are multiple types of warping that are selected on the basis of requirement, we apply spherical warping because we are making a 3D environment that covers the whole 360 portion of any area.

After applying warping on all numbers of images we receive all spherical warped images and transform the top left corner of images. Those corners also contain some negative values that are estimated by considering the final resultant panorama size and scale based on the center of image.

All points that lie on the left side of center width are considered x-axis points as negative and all points that lie on the right side of center width are considered x-axis points as positive. Y-axis points are treated in similar manners in case of above and below. After applying a warping corner all overlapping regions are removed and we get the whole panorama without any overlapped region with proper alignment. All alignment and ghosting issues are produced from here due to wrong estimation of the top left corner. And in most of the cases those wrong corner predictions are held due to low accuracy and homography transformation estimation. As we discuss all overlapping regions removed when we place each image in another plane by using corresponding corner information and as we know each next image is placed on the previous image at corner position and this is how we select overlapping regions only from the right image.

There would be some procedure that defines the selection of portions based on quality that is not performed by the warping method.

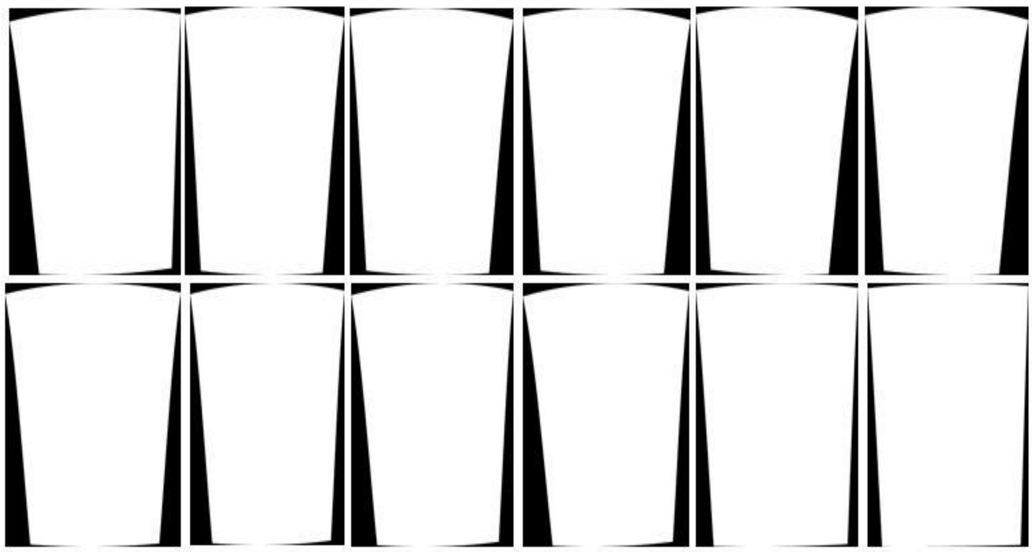

Figure 7: Warped Mask

For removing distortion we warped images of sample data as shown in above two rows. All images are warped in spherical form for covering the camera parameters affect and removing alignment error.

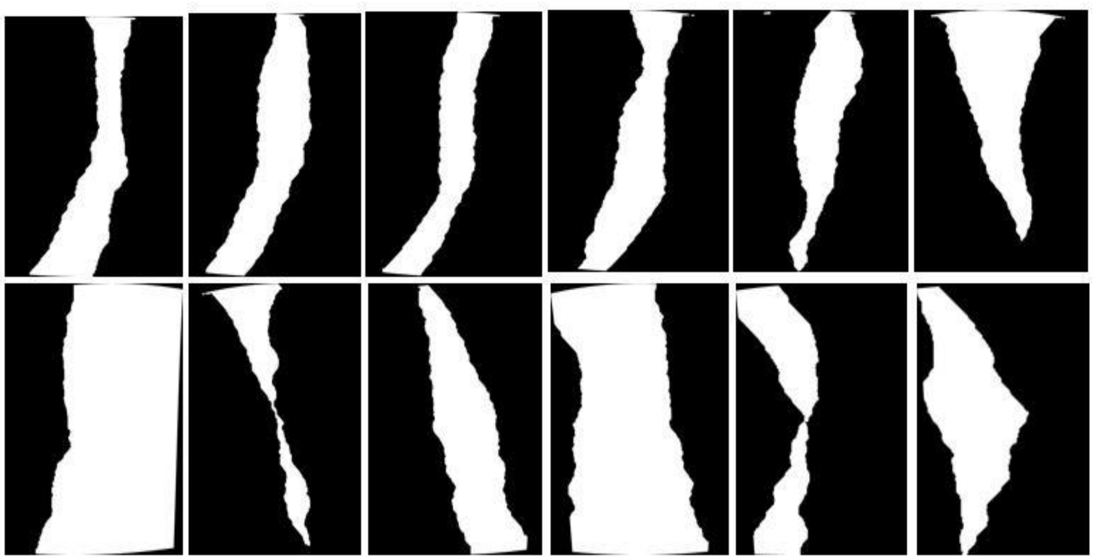

Figure 8: Seam Mask

For removing parallax error and selecting the important or accurate area from different images we apply seam cutting as observed in images that select the area of final plan that are captured from source images. By combining all seam cutting images we build a final plan of panorama.

3.6 Seam line

For handling the issue that we face due to straight line warping so we implement a seam finding algorithm, that algorithm estimates the line that produces better quality results. As we know that are ghosting artifacts in panorama become the most challenging topic and outdoor environments due to wrong selection of image portion.

We will also resolve those ghosting artifacts by getting the zig zagging line that separates two images and select the portion that enhances the panorama quality.

This algorithm takes input images that are wrapped by wrapper and predicted corners as well and outputs the same images with seam cutting.

This step of image stitching is the one of the main contributions of our proposed method that will contribute a lot to enhancing the previous stitching results.

By using seam estimation we are able to decide which portion of the image takes place in our final panorama and which portion of the image is not more necessary.

Figure 9: Resolution Differences

By removing all alignment errors we generate some new errors that produce some resolution exposure and unbalancing and reduce the visual artifacts of the final panorama as seen in the attached image. We observe the prominent zig zagging lines that are due to proper seam cutting lines for minimizing the alignment issues from panorama.

3.7 Wave correction

As seam lines estimate the wavy lines images that have some outliers and we need to smooth them as edges are smooth before attaching them for enhancing the quality of result and better adjustment. In similar manners we apply wave correction technique on seams lines that focus only on edges and apply smooth filters on them for making better and quality adjustments with other images.

3.8 Resolution changes effects

By extracting features, homography and seam lines we are successful for removing the alignment, ghosting, distortion and all other placing issues related to stitching. But after placing multiple images into one plane we have a resultant panorama that has multiple resolution changes, exposure changes with attaching seam lines as well. Each portion of the panorama has a different color and resolution that loses the quality of the panorama and we are unable to present this artifact less panorama with high resolution difference. There are multiple smoothing filters that are conventionally applied on images after stitching but their performance is not good in our case because we have a lot of changes with different differences.

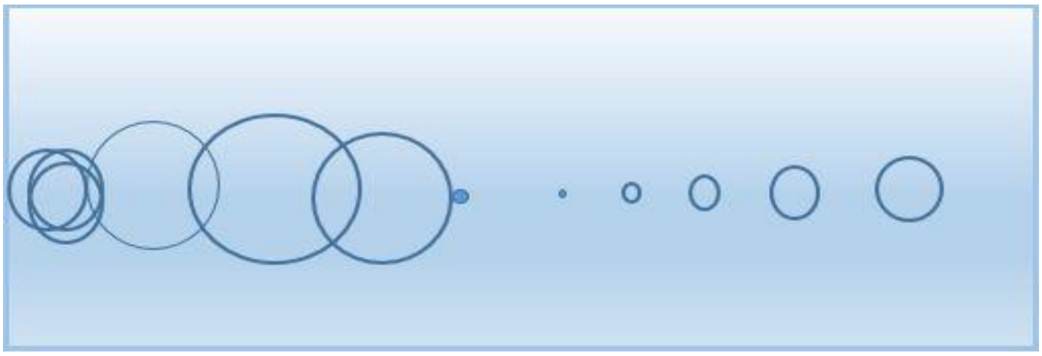

Figure 10: Ordering of images by Algorithm

We have two ordering of images in our algorithm one is the processing order that is same as passed by user and the second one is due to matching accuracy, In above image we saw some small and large circle that are increase in their size as our input images count are increase but the location of their circle are set according to their matching accuracy.

The lowest matched images pair are always placed at the corner of images.

3.9 Compensator

Before applying any smoothing techniques on the generated panorama we need some compensation between high resolution changes that somehow reduce the work of smoothing filters and enhance the chances of better smoothing results. Compensator is a gradient based technique that reduces high changes in resolution and increases balance between brightness, resolution, exposure and color and reduces large ups downs by taking gradient.

3.10 Smoothing

We apply smoothing on iterative manners first when two images are stitch we apply weighted smoothing filters that are stronger at top left corner place and lighter as procedure to left and right side. This process continues as images are stitched and appended.

When new images are appended we apply those smoothing filters twice, one for according new and previous images and second one is for all previous images. This is how we are able to handle multiple resolution changes and remove all color effects.

Smoothing filters contain values that are Gaussian distributed according to their corner/center point and we simply multiply this design filter with our process stitch images.

Figure 11: Stitching of images without cropping

Here we have our final image that is stitched by our algorithm, but we see some black regions in the boundaries of the panorama that are due to spherical warping or user vertically movement of the captured camera and we must remove those black region to make them visually good and effective.

3.11 Cropping

Stitching extra black regions are produced at top and bottom on results due to spherical warping that we need to remove for producing presentable results.

We are not compromising on the quality of results even if we lose some portion of the final image. That's why we need to find the lowest portion of black region and then cut off the resultant panorama from here.

For finding an accurate boundary of the panorama we convert our resultant panorama into gray scale and then apply canny edge detection on them. After applying binary thresholding techniques on the generated mask we get all contours and their hierarchy that are set based on area of creed contours. We apply a sorting algorithm on all contours by using their area and then select the highest contours values. Those created contours are polygons that need to be converted into optimal rectangles. The selected rectangle are used for mapping the resultant image and at the end we remove all black region from panorama with loss of some boundary information but with better quality.

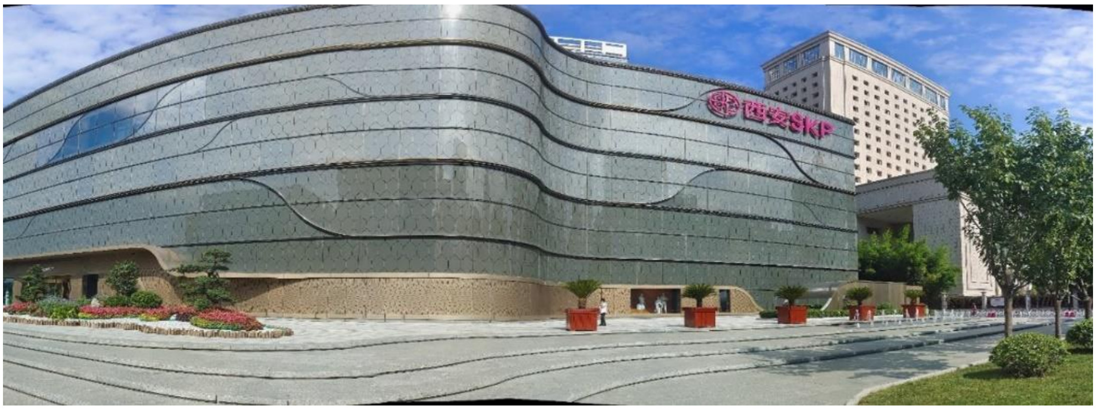

Figure 12: Cropped Black region from panorama

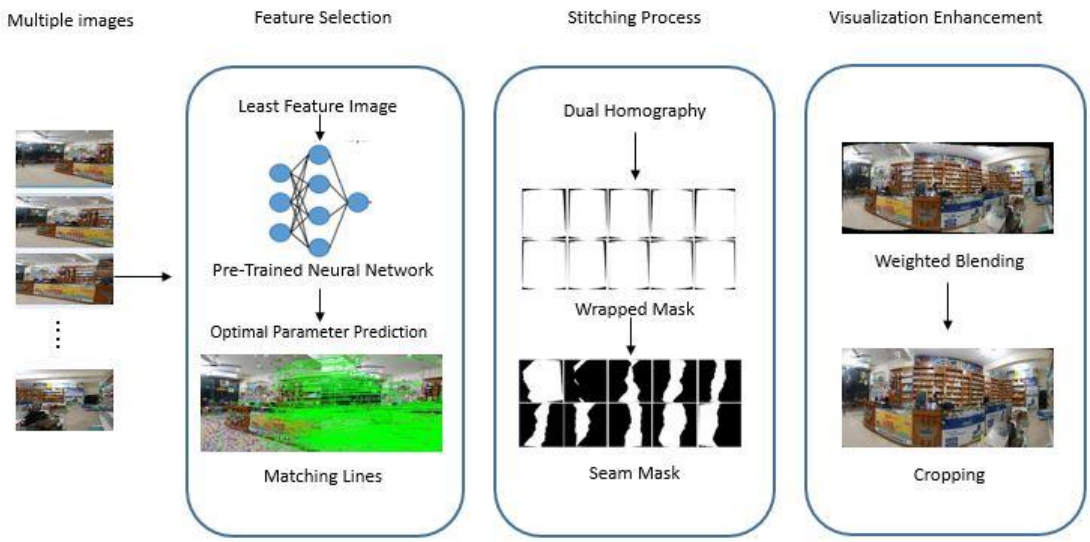

Figure 13: The framework of the proposed method

CHAPTER 4

RESULTS AND DISCUSSIONS

Our main goal is to stitch the images that cover whole 360 views on which all previous method to fail. If some are able to stitch that kind of images but they have artifacts and alignments issues and take much time to get the results. We primarily discuss some cases in which our algorithm work so efficiently.

Here we stitch thirty six images that are not captured in only one direction or with a small tiled camera, here we have images that are captured vertically and horizontally with large tiled camera and camera parameters are more frequently changed more than with other samples. This example is very challenging for stitching and almost all state of the art algorithms fail to get results on them, but our proposed model produces promising results on them and we also visualize that we have results without any merge and prominent artifacts. Also, our proposed model is not dependent on image count or the capture device, it has a capability to perform well on any number of images or any device capture of images.

Figure 14: Resultant panorama of 36 images

We perceive image that the sample images contain floor and trees at background that has not huge differentiation and contain almost similar structure that is most challenging problem in state of the art stitching algorithm but our designed model are capable to process this types of data in an efficient way and produce good stitched panorama with optimal alignment and smoother resolutions changes.

Figure 15: Resultant Panorama of 7 images

We are working on stitching that provides a whole 360 environment view without any external hardware resources, here we have images that cover the whole 360 view of the room and our proposed model stitched them in the proper way. If we combine both left and right edges of the panorama the room 360 view is completed without any artifacts that are not possible with other state of the art stitching algorithms.

Figure 16: Resultant Panorama of 12 images

Figure 17: Resultant panorama in the scene of Library

Figure 18: Resultant panorama of outdoor environment

4.1 Visual comparison with the State-of-the-art Methods

We have one sample that captures images in a zig zagging way and we perform stitching on that type of captures and compare the results with other existing and state of the art algorithms.

Figure 19: Image Sample with Zig Zagging way

As we can observe, the result of GSP starts stitching from the left or right side in parallel manners and produces a lot of alignment errors on center frames. APAP is the most promising model and the result of this is much better than GSP or SPW but still it contains some issues like frame rotation transformations are not accurate in panorama. SPW totally mixed up all images and also removed some images from results that are present in sample images. The resultant panorama of our model is most accurate and optimal stitching results with comparison of others. Our results handle alignment and rotation changes in that way that enhance the quality of results and provide good visualization w.r.t others results.

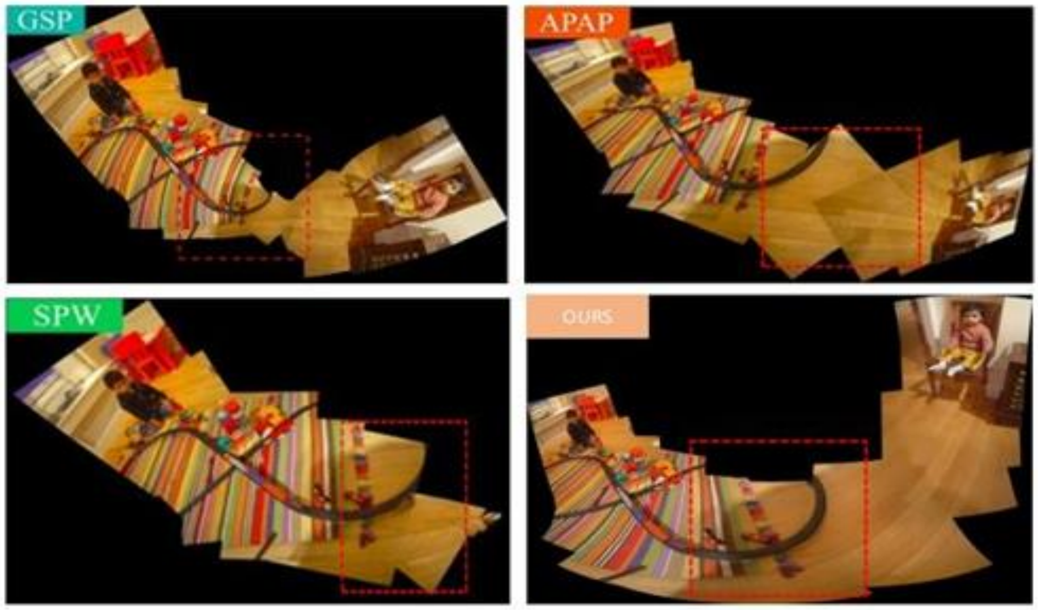

Figure 20: A Comparison result with GSP, APAP and SPW

Here we compare the result of the sample image with the APAP algorithm and observe that the blending artifacts in APAP are not accurate in the zoom portion but this is efficiently handled by our algorithm. Our algorithm blend the resolution changes in such manners that reduce the stitching effects and make results visually better.

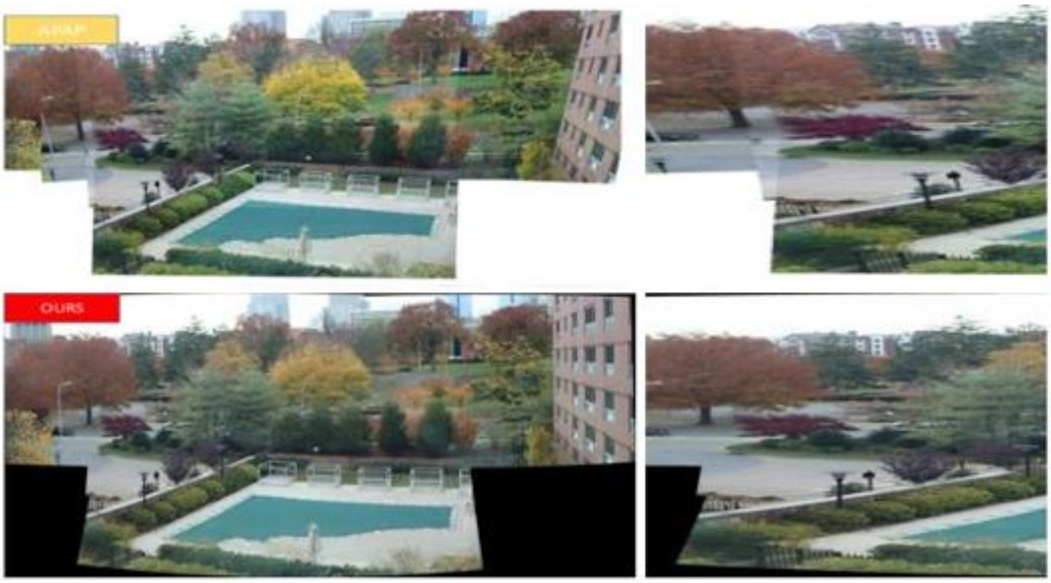

Figure 21: A Comparison result of Stitching 4 images with APAP

In the analysis below we compare the results of SPW, APAP and our model. We can easily observe that the shape of doors are tilled and stretched in previous methods named as SPW and APAP. Also, on the bottom of the panorama we zoom some wall portion of the image and conclude that the clocks are distorted due to parallax error in both mentioned methods. Those two errors are large and prominent errors that cannot be ignored and add wrong visual artifacts in results. For better evaluation we do main focus on those two portions of panorama that are stitched by our algorithm and analyze that the shape of the door remains same as in the captured images and the clock portion is clearly merged without any parallax effect**.**

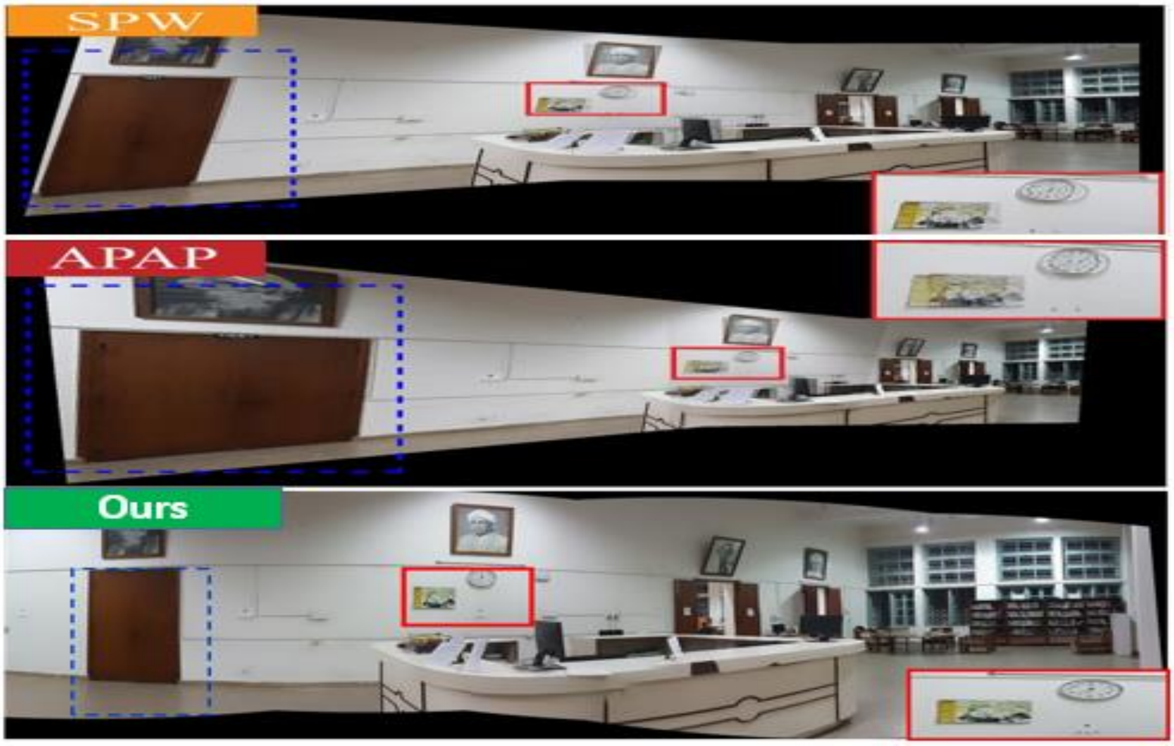

Figure 22: Comparison result in the scene of Office with SPW and APAP

In the below image we zoom in on a specific portion of panorama that is obtained by GSP methodology and the same portion is cropped from our result on a similar data sample. We examine that the parallel lines are show some wavy curves in panorama that are getting from GSP algorithm but on the same time those lines are accurate in panorama that are acquire from our algorithm, those mention results show that the accuracy of our model in different cases.

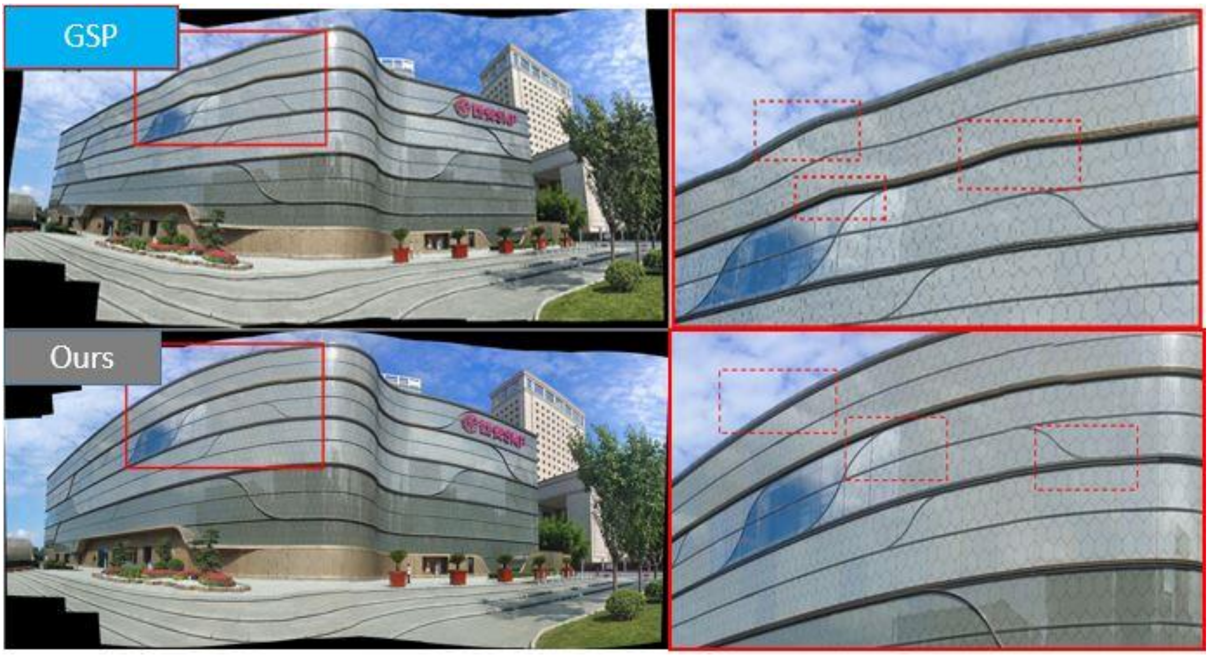

Figure 23: Comparison result with GSP algorithm

4.2 Quantitative Analysis

At present, the mostly used quantitative assessment index for stitching is MSE. In this method feature is extracted from the overlapping area of composite image. Table. 1 shown Mean square error that is basically the pixel wise difference between two images. In the given equation y is original patch and $y'$is the patch that is extracted from stitched panorama and x is the total number of sample images. In our case it has only one sample that's why N=1.

$$MSE = \frac{1}{X}\sum_{i=1}^{N}(y_i - y_i')^2 \quad 10$$

For evaluating the stitching models according to commutative difference shown in Table. 2 create histogram of first patch of resultant panorama F1 as FH1 and for second patch of second resultant panorama F2 as FH2. By taking histogram and probability difference it calculate commutative difference.

$$FH1 = hist(F1) \quad 11$$

$$FH2 = hist(F2) \quad 12$$

$$FH - diff = FH1 - FH2 \quad 13$$

$$FH - prob = FH1 \oplus FH2 \quad 14$$

$$C - diff = \left(FH - \frac{diff}{10}\right) + (FH - prob) \quad 15$$

Table 1. Quantitative Evaluation of different stitching method using MSE

Dataset	MSE Value	
	APAP [4]	OURS
Sample 1	93.97	**82.07**
Sample 2	73.13	**66.50**
	LPS [8]	Ours
Sample 3	91.00	**82.07**
Sample 4	93.00	**66.50**

Table 2. Quantitative Evaluation of different stitching method using Commutative Difference

Dataset	MSE Value	
	APAP [4]	OURS
Sample 1	0.54	**0.17**
Sample 2	0.45	**0.30**
	LPS [8]	Ours
Sample 3	**0.33**	0.35
Sample 4	0.09	0.05

The quantitative assessment results in Table 1 and 2 show that the performance of our method is better than that the other algorithms. Even through the commutative difference of LPS [8] is good than our method in one case, but the visual effect of our algorithm is better.

DISCUSSION

For achieving the better results we were trying to use camera parameters that are used in intrinsic matrix. Currently we are doing estimation of those parameters by just capturing the matching information without any hardware or environment knowledge. Those parameters help us to accurately remove distortion from images and resolve all artifacts that are due to the capturing process. But for getting this hardware information we need to acquire data manually with different hardware changes that are not possible for a single user. That's why we do stitching by estimating the intrinsic matrix that is based on images matching information. This experiment will be achieved in the future when we have resources for getting enough data.

We were trying to set the location of images in the output plane in similar manners as are passed by user and the ordering remains the same, but for achieving the quality results we always place low matched images on the edges of panorama. By improving the matches' confidence we can change the ordering according to user input but for this purpose we need to specifically work on matching algorithms that we will list down as our future recommendations.

There are multiple types of warping that we can explicitly decide for our stitching purpose and we can compare the results changes according to user requirement. We tried 3 to 4 warping method names as cylindrical, fish eye, planar and spherical. After analyzing the results of all warping methods we decided to go with cylindrical because we are basically providing a 360 view of any environment that is usually followed horizontally and vertically translation in frames. But the artifacts of resultant panorama are also dependent on warping selection and we did not want to compromise on quality. Quality w.r.t warping comparison should help us for selecting the better quality results.

As we know we calculate multi homography for removing the parallax error mostly from outdoor environment and the count of homographies are similar as in APAP but, for removing the complexity of model we need to reduce the count of homography and make them hyper parameters that will change according to complexity of sample data. We will further do exploration on the count of homographies and their effects on the resultant panorama and then decide to make them part of optimal learning parameters [33].

CHAPTER 5

CONCLUSION

This thesis processes an image stitching method using a small neural network that is capable of predicting the optimal parameters that will help in further processes. First the small neural network is trained to receive some low matching confidence images and find the optimal parameters such as features finder parameters, matches count, their confidence and many more. And then we use those predicted parameters and find features from all images and later those feature descriptors are used for finding matches. For removing the parallax error from final panorama objects we estimate multiple homography matrices and then apply all homographies according to their selected regions. This is how we are able to remove stitching alignment, translation and rotation issues from results.

For balancing the resolution artifacts we apply a compensator with a blending filter that first tries to balance and compensate for the changes between resolutions that are mostly prominent at the edges of the stitching corner and then some of the changes that are not handled during compensation are handled during blending. We apply weighted blending by giving the information of the stitching corner that will do most of the focus on those corners and smooth gradually as far from those corners. This is how we get a final panorama that is free from alignment, rotation, parallax, resolution and other stitching errors.

We run our code on similar dataset that are used in other state of the art image stitching research and compare the performance by visually comparing the panorama and w.r.t time that are used during processing. We conclude that the performance of our proposed model is much better than with other state of the art methods in terms of alignment, ghosting, parallax issues and resolution refinement and it is two times less complex with previous methods that will help us to deploy them in a real time environment. We have some future recommendations that we will implement and try to enhance the current progress in some other direction

CHAPTER 6

Future Recommendations

Many efforts were made in the study to provide some additional elements for a better understanding of the concepts studied in the thesis; however, some questions unanswered, and some additional ideas originated during the research period, for which the following recommendations are discovered for future work.

- In future we can further save the camera parameters directly during capturing the images and we can use as intrinsic matrix for transformation purpose rather than estimation.
- We can also perform others operations on this stitch images just like detection, segmentation, counting of objects and get more information.
- In further we make application of this process that provide 3D view of any location in just one view without using any advance camera or extra resources.
- We can also take help from this panorama images for self-driving car and other automatic applications like this.
- In future we make a pipeline that make our process parallel as possible by using multiple cores and threads operation that boost up the processing speed.
- Build a proper data set that contain multiple counts samples images for proper testing and analyzing the results of our designed system.
- Tripod based application are designed for capturing the data set that will help us for reducing the chances of alignments and resolutions changes artifacts during stitching and may produce good quality results.

CHAPTER 7

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