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Image mosaicing: A deeper insight☆

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ABSTRACT

Image mosaicing is an effective means of constructing a single seamless image by aligning multiple partially overlapped images. Over the years, the research attention on mosaicing has increased a lot due to the growing applications and subsequently, many algorithms related to mosaicing and its contributing steps have come into existence. Though, the varied approaches for mosaic generation are effective, several difficulties arise in each step of mosaicing which need to be addressed specifically. The aim of this review is to provide an insight into the existing mosaicing algorithms, along with their merits and shortcomings. Additionally, the manuscript provides a classification of these algorithms based on their domain of processing, application, image type, and visual attributes. Furthermore, a comparison among various mosaicing methods is presented to find out which algorithm works best for a particular application and image type. Finally, the paper is concluded with a highlight on future research directions.

1. Introduction

Image mosaicing has received a lot of interest in recent years for its diversified applications in computer vision and graphics. The basic mosaicing framework initially used panoramic cameras and fisheye lenses [1]. With the advent of digital cameras and the need of wider pictures, computer vision techniques were introduced for mosaicing of images. Presently, image mosaicing is not only limited to panorama creation from thousands of partially overlapped images, but also it has found exciting applications in image editing and compositing from non-overlapping images. Many mosaicing and related approaches which earlier relied only on computers, can now easily be implemented on low-cost electronic devices.

For the creation of a mosaic, multiple overlapping images of a scene are aligned to generate a single image with wider field-of-view (FOV). Image mosaicing provides the possibility to reduce noise, extend FOV without compromising the spatial resolution and render the different images of a scene into a common composite image. These mosaics are required in various areas of applications such as satellite imaging/remote sensing [2], medical imaging [3,4], virtual reality and games [5], image editing [6], visual effects [7], biometric [8,9], surveillance and monitoring of industrial plants [10], and underwater surveillance [11,12].

There are two specific requirements for a good quality image mosaic. First, the images should be aligned properly (accurately) i.e. there should be geometric similarity between the input images and the generated mosaic. Secondly, the transition region between the mosaiced images should be smooth and should have least photometric difference.

A simplified representation of image mosaicing steps is shown in Fig. 1. Here, N images are used to demonstrate the formation of a final image mosaic. Fig. 2 shows a panorama of a street side which is created from 107 images. There are three main steps for image mosaic generation: image registration [13], image warping/reprojection [14], and image blending [15,16]. However, there are some computer vision and graphics applications where registration or warping is not required [17]. In such cases, image regions are merged with each other to produce a new image or some amazing visual effects. However, some of the recent compositing methods use warping [18] and feature matching [18,19] for image compositing. Image registration aims to find geometric relation among the series of images to align them accurately and estimate the motion between the images due to different viewpoints or camera displacement [20]. Firstly, the images are aligned using a common global coordinate instead of the local coordinate of each individual image of the scene. In the next stage, the aligned images are projected over a common compositing manifold for warping [21]. The compositing surface/manifold provides a global frame to the aligned images for the generation of a single image mosaic. When two images are registered and projected onto a common surface then there is creation of perceptible edges in the overlapping region. This makes the

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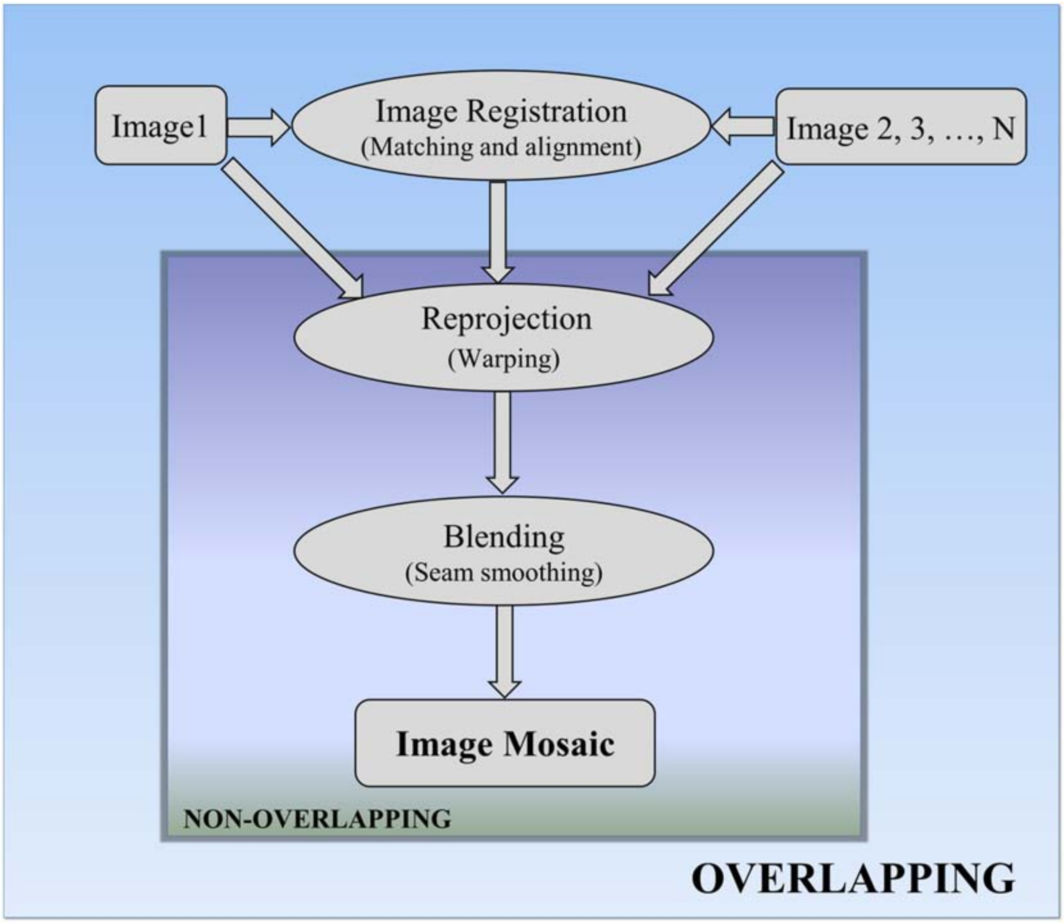


Fig. 1. Simplified representation of steps in creating an image mosaic from a collection of images.

mosaic visually annoying. Therefore, in the third stage, the warped images are blended with each other to remove any visible artifacts in the overlapping part of the warped images [22]. Image blending plays a key role in removing such artifacts by smoothing the seams. An appropriate blending function is selected to mitigate the visible artifacts for the generation of visually appealing image mosaics.

1.1. Present status of mosaicing and prominent algorithms

Over the last few decades, the number of image mosaicing algorithms has grown significantly. Most of the mosaicing algorithms address the alignment of images [24,25], blending of the images [4,26,27] or the combination thereof [9, 28, 29]. For accurate alignment of images, methods like [30], [31], [32] and [33] use correlation between images whereas [34,35] use salient features for image alignment. Blending of images for mitigating the effects of seams has been of great concern in the literature [36,37]. Consequently, numerous blending techniques [38–41] have been proposed to address all sorts of blending artifacts. Some techniques [28,29,42] address both registration as well as blending. Furthermore, many software with built-in mosaicing quality like Photoshop, Autostitch, and Microsoft image composite editor (ICE) have come into existence. Image mosaicing has included a lot of computer vision and graphics related [18,43–45] application in addition to its primary application of panorama generation with increased FOV. Although image mosaicing has been treated widely in literature, many challenges still remain to be addressed.

1.2. Challenges of mosaicing

Image mosaicing is a challenging area of research due to the difficulty in good quality mosaic generation. It is still elusive to find solutions to all the problems such as illumination variation, camera rotation or zoom, moving objects in the scene, noise during image

Fig. 2. A panorama created from multiple street side view images [23].

acquisition, and multimodal imagery. More specifically, illumination variation between images can create prominent seam between images due to difference in pixel intensities. Camera motion and zoom pose problem during alignment of images. Moreover, moving objects in the scene can cause ghosting (duplication of image objects) or double contouring (blurry boundary around the object) in the mosaic. Furthermore, noise introduced during image acquisition reduces the clarity of the mosaic. As a result of these effects, the final mosaic may not look visually pleasant and contain a lot of artifacts in it. Therefore, these factors are required to be handled carefully by using a robust mosaicing algorithm.

1.3. Need of classification

With the advancement in computer vision techniques, image mosaicing methods have come a long way since the era of bulky panoramic cameras. Today, almost anybody can use these methods to generate a panorama with apparent ease. Different applications require different mosaicing algorithms depending on the specific challenges involved. For example, underwater images need image enhancement as a necessary pre-processing step which may not be desired in case of scenery images. Likewise, the speckle noise reduction required for ultrasound images and some satellite images may not be needed in biometric or document images. In the same way, the consideration of camera rotation, scaling, zooming, etc. is crucial for the registration of partially overlapped images but these are not a part of non-overlapping image mosaicing i.e. image compositing.

Research papers like [29] and [46] discuss various techniques on mosaicing based on registration methods or blending approaches. In the recent work [18,19,47], the authors have presented a comprehensive survey on methods for image compositing. Despite these surveys, none of these papers classify the image mosaicing methods on the basis of the attributes which could give a clear picture of the specific methods that will work for a particular set of images. For the users, the choice of mosaicing algorithms often causes confusion. Therefore, the purpose of this research work is to give an exhaustive review on different mosaicing methods based on the underlying concepts, types of images and the mosaicing applications. The comparative study of these algorithms has also been discussed so that the selection of specific methodology suitable for the image type becomes obvious.

1.4. Contribution of the work

The contribution of the present work is threefold:

1. A comprehensive review on existing mosaicing related algorithms is presented.
2. A detailed categorization of the mosaicing algorithms based on important classification attributes is introduced.
3. Comparison among the different mosaicing algorithms considering their challenges, methodology, advantages, and shortcomings is discussed for easy selection of specific algorithms required for the mosaicing application in hand.

To the best of our knowledge and belief, this work is the first attempt to provide an extensive survey on mosaicing algorithms with more than 100 literature works reviewed.

The content of the paper is arranged as follows: Section 2 presents a comprehensive categorization of image mosaicing algorithms. The different classes of image mosaicing are elaborated in Section 3 along with the implementation details. Section 4 discusses a comparison among the mosaicing algorithms based on their challenges, applicability, and feasibility for specific purposes. Finally, the review is concluded with the scope of future work in Section 5.

2. Mosaicing taxonomy

The algorithms for mosaicing of images are diverse. To classify these algorithms into different categories, we have used the

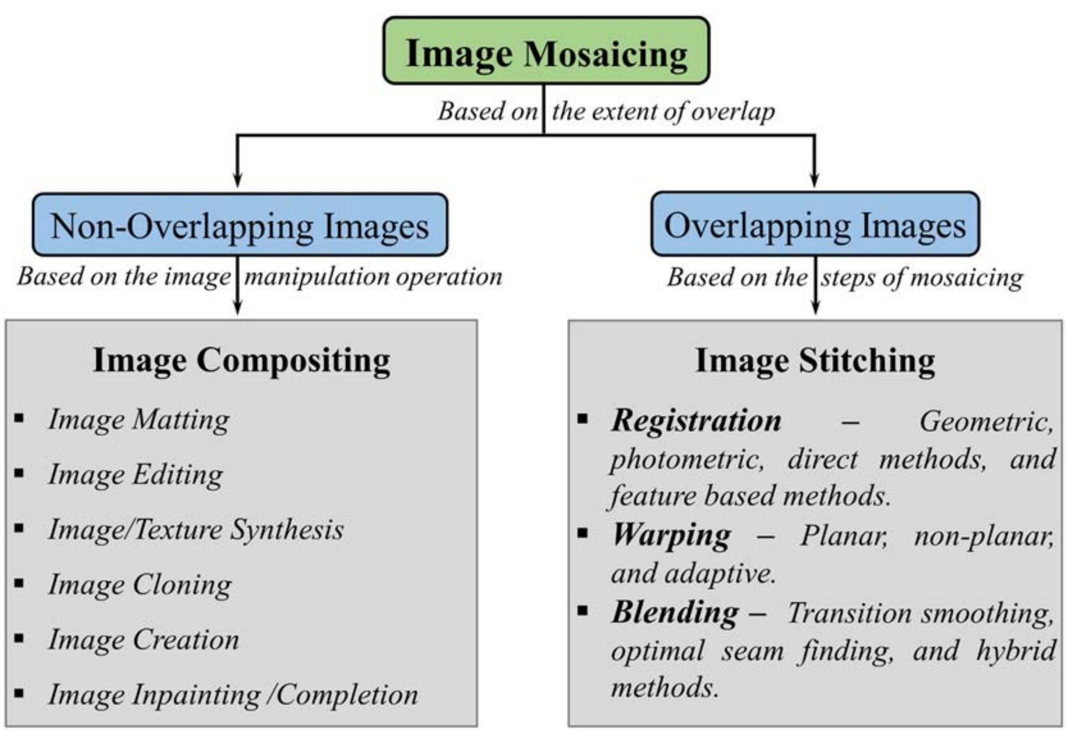


Fig. 3. Classification of image mosaicing methods based on the extent of image overlap.

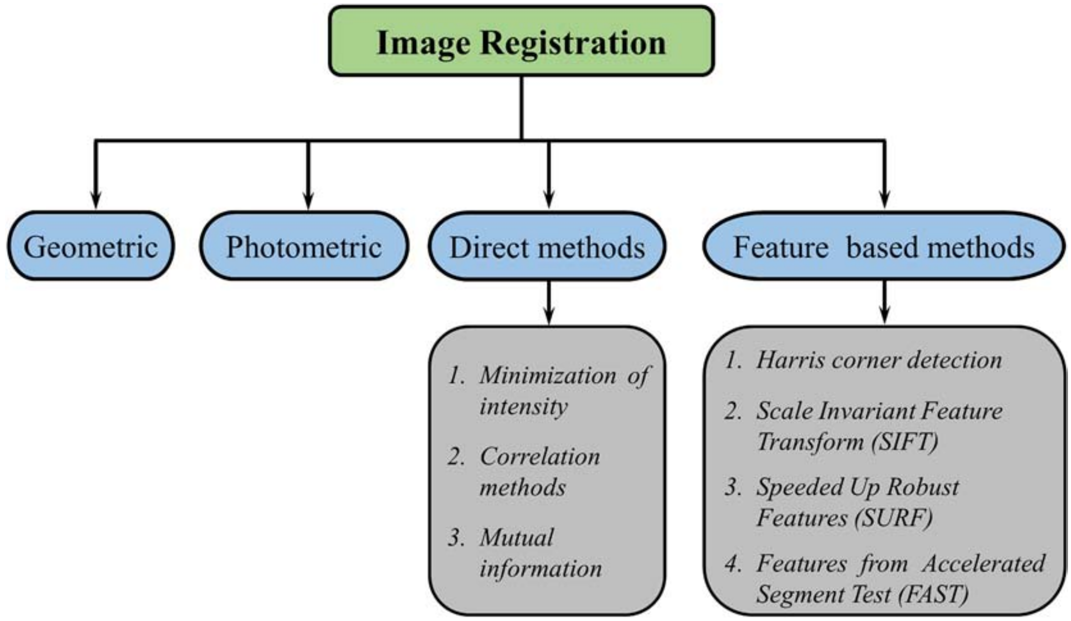


Fig. 4. Classification of image mosaicing methods based on the alignment of images.

extent of overlap as a first classification measure. Depending on the extent of overlapping between images, these techniques are categorized as *non-overlapping* and *overlapping* image mosaicing. Non-overlapping images do not have common region of overlap between them and are mostly different from each other. However, these images may represent parts of the same scene to be mosaiced [48]. Non-overlapping image mosaicing is often referred to as *image compositing*. On the other hand, overlapping images contain common regions or partially overlapped region which have similar features. Based on these features, the images are aligned and registered with each other. Two or more overlapping images of different parts of a scene can be mosaiced to represent the complete view of the scene. Over the years, the mosaicing of images have extended to mega and gigapixel images [29,49,50]. Mosaicing of overlapping images is called *image stitching* or simply *image mosaicing*. For the sake of clarity, we have used ‘image stitching’ to refer to mosaicing of overlapping images throughout the paper. Fig. 3 represents the classification of mosaicing methods based on overlapping region.

Image mosaicing has been explored to a great extent, based on the different techniques used to align the input images. These approaches are referred to as registration methods. A classification considering the various schemes for alignment of images on a reference surface is given in Fig. 4.

Overlaying the images on a common manifold does not always generate flawless mosaics. Discontinuities are often visible in the

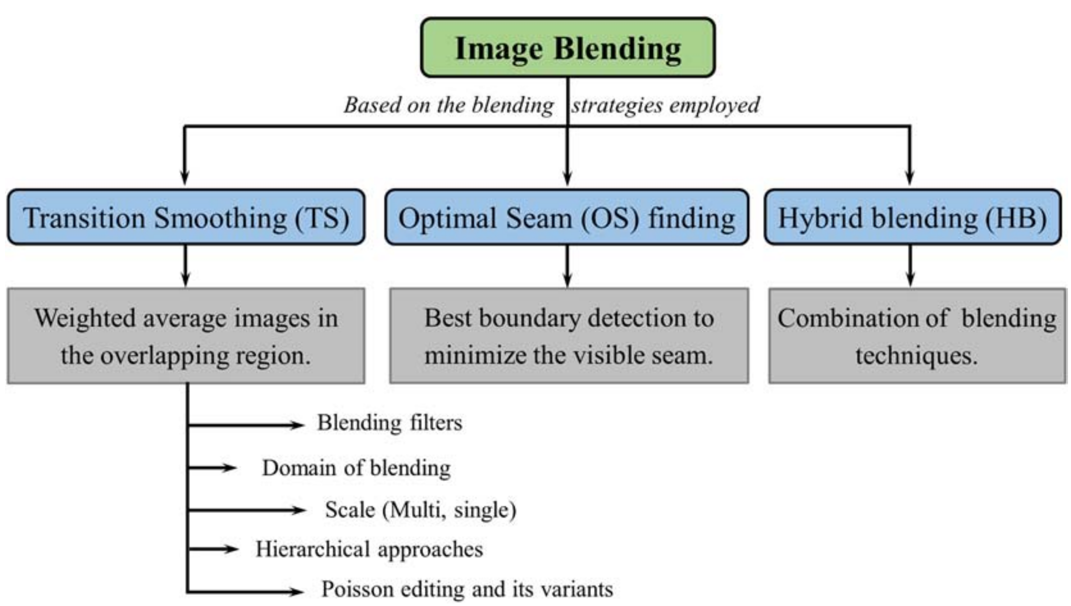


Fig. 5. Classification of image mosaicing methods based on the blending approach adopted.

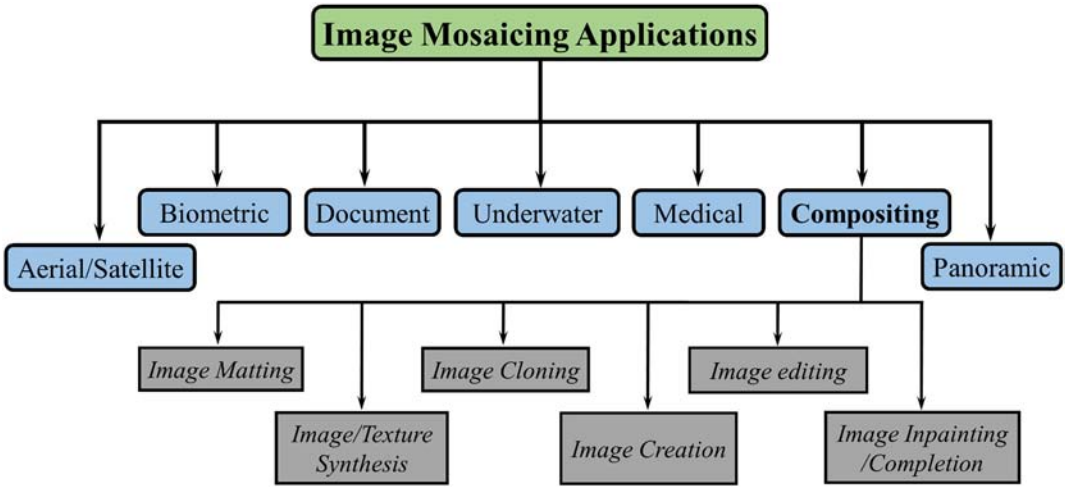


Fig. 6. Classification of image mosaicing methods based on the area of application.

region of overlap resulting from misalignment error or photometric difference between images. Blending algorithms, therefore, play an important role to alleviate such discontinuities. Fig. 5 shows the classification of mosaicing algorithm based on blending strategies applied for mosaic generation. The blending algorithms can be classified into three groups: transition smoothing (TS), optimal seam finding (OS), and hybrid blending (HB).

Mosaics can also be of two types based on the motion of individual frames. If a mosaic is generated from still pictures it is called static mosaic and if the time constraint of frames is considered then it is called dynamosaics [51].

In the context of particular application of mosaiced image, the existing algorithms can be classified as panoramic, medical, document, underwater, aerial or satellite, biometric, and compositing based applications. The detailed classification based on specific application of the mosaics is given in Fig. 6.

The details of these classes are given in the forthcoming sections.

3. Classification attributes for image mosaicing algorithms

Type of image, area of application, registration, and blending techniques employed are some of the main factors based on which the mosaicing algorithms have been classified. These factors for classification of mosaicing techniques are described in detail in the following subsections.

3.1. Based on the extent of overlap

As described in Section 2, the input images can be either non-overlapping or overlapping. In literature, the terms compositing, stitching, and mosaicing are used interchangeably. However, in this work, we use the term '*image compositing*' to refer to non-overlapping image mosaicing and the term '*image stitching*' is used to indicate mosaicing of overlapping images.

3.1.1. Non-overlapping

Image compositing is an important research topic in computer vision and graphics. The fundamental aim of image compositing is to form a new image by merging multiple source images that may or may not be alike. In most compositing approaches, the object within the images are very important, and the research focus is on how to blend the objects of one image with the background of other seamlessly to get visually pleasant image or some visual effects.

The application domain of image compositing includes photo-editing [52], films and television [53], animation, 3-D virtual character [18], missing part completion [54], correction by fixing defects [55] and so on.

The algorithms for image compositing are divided into the following groups: image matting, image editing, image and texture synthesis, image cloning, image creation, image inpainting and completion. Each class has its own set of challenges as well as methodologies explained below.

3.1.1.1. 1. Image matting. Image matting is a key approach used for the estimation of foreground in the images as well as videos for editing/compositing operations mainly in films and animation. Matting approaches use the matte weight for linear interpolation of source and target images. To generate an image composition $I(x,y)$, a foreground image $F(x,y)$ and a background image $B(x,y)$ are blended with alpha matte $\alpha(x,y)$. The equation is given as,

$$I(x,y) = \alpha(x,y)F(x,y) + (1-\alpha(x,y))B(x,y) \quad (1)$$

Here, the unknowns F, B, and α are required to be estimated.

i) Natural image matting. In order to get a good matte, the user supplies a trimap that divides the image into three parts: 'foreground', 'background', and an 'unknown region'. Most of the natural matting approaches [56–58] use sample gathering and matte estimation where the known foreground and background pixels are then sampled to estimate the matte in the unknown region. Bayesian matting [56] is one of the most successful matte generation technique in this class. An extensive survey as well as comparison on natural image matting algorithms is provided by the authors in [56]. However, these techniques are based on the color sampling which produces errors for complicated scenes. Moreover, it is extremely difficult to get a correct matte without additional user supplied information.

ii) Blue screen matting. Problems and solutions to separate a desired foreground from a constant background have been presented in [59]. Here, the constant background often has blue color that separates the object from the background and, therefore, it is called blue screen matting. In case of blue screen matting, the accuracy of matte results depends on the user's involvement in controlling and adjusting the results.

iii) Difference matting. Difference matting [60] depends on two images for matte generation. A foreground image and an image without foreground, but with the same background. The difference between these two images results in a matte.

iv) Video matting. Bayesian matting [56] was extended to develop video matting framework [44]. To generate a matte, the user supplied trimaps are interpolated using a bi-directional optical flow algorithm. Additionally, the method also demonstrates smoke matte extraction.

v) Poisson matting. Poisson matting [61] is a semi-automatic matte generation method. In this approach, gradient field of matte is estimated using the input image and then Poisson equation is solved to obtain matte from its gradient field. The method reduces the misclassification error resulting from color samples in complex scenes. However, it fails if the foreground and background colors are similar. Nevertheless, user interaction becomes integral when the gradient of matte is highly interweaved with the foreground and background gradients.

Thus, matting algorithms are best suited for compositing furry objects. The accurate matte generation helps in handling color mixing problem effectively. However, the problem with matting is that user involvement is always needed either for trimap generation or for providing brush strokes. Moreover, these techniques do not give a natural appearance to the composites when source and target images have different color or texture. This is due to the reason that the background and neighboring pixels of the foreground object are removed completely.

3.1.1.2. 2. Image editing. Image editing encompasses a wide range of image manipulation techniques. *Poisson image editing*[6] is a reference standard that provides the capability and ease of using various editing tools for a series of compositing operations. Here, the image manipulation is based on gradient fields of source and target images. The final composite is recovered by solving Poisson equation. The method has been used by researchers for more than a decade. Consequently, various modified editing techniques were formulated based on Poisson editing and its variants. However, the inward boundary interpolation while solving Poisson equation leads to an undesirable phenomenon called *color bleeding*.

Methods such as [50,62], work well for smooth interior and suitable boundary, without the need to solving expensive Poisson equation. Several techniques have been introduced to improve the performance of image editing in gradient domain [63–65]. Jia et al. [17] introduced *drag-and-drop* pasting by optimizing the blending boundary to reduce texture and color difference between input images. To remove color inconsistencies for producing more realistic image composites, Sunkavalli et al. [66] use multi-scale image harmonization technique. Georgieve [67,68] developed methods to handle lighting and illumination variation including defect removal for seamless cloning of images. For producing high quality image, Shen et al. [69] blend multiple exposure images using a novel boosting Laplacian pyramid (BLP). Their method is based on the boosting of detail and base signal guided by exposure weights.

The problem with most of the gradient domain methods is *color bleeding*. Due to color bleeding, the color of the inserted object changes in the final composite which is not always desirable. Moreover, texture difference between input images leads to failure of the process. Current methods [70–73] address these problems and suggest solutions to the same. Yang et al. [70] provide solution to these issues by presenting a variational model, distance enhanced random walk, and a multi-resolution framework for natural image composition. A gradient-domain compositing technique is proposed by Tao et al. [71] to reduce the extent of color bleeding. Their method is robust to inaccuracies due to low-curl boundary, still it sometimes results sharp color change as well as discoloration in the composites. Zhang et al. [72] provide a solution to texture inconsistencies in gradient-domain cloning, but user involvement is required for supplying foreground and background strokes. Recently, Henz et al. [73] offered color control of images by membrane modulation. However, none of these methods solve the problem completely.

3.1.1.3. 3. Image and texture synthesis. Generation of synthetic texture is an active research topic in computer graphics. The primary objective of image/texture synthesis is to generate a new texture image such that it is sufficiently different from the example texture image yet still appears as it was generated from the example texture image i.e. it emulates the generative process of example texture. De Bonet [74] proposed a two phase multi-resolution technique for sampling new textures by treating the input texture image as probability density estimates. The method, however, models simple structures and the use of local constraints limit the modelling for complex visual structures. Efros and Leung [75] developed a texture synthesis method based on non-parametric sampling and model the texture as a Markov random field (MRF). The problem like garbage growth or verbatim copying of textures usually occur when sample image is not big enough and contains too many different type of texture elements (texels). Several methods have been developed as variation of [75], including *image quilting*[76] and *image analogies*[77]. A texture synthesis algorithm based on graph cut stitching of patch regions from sample images is proposed by Kwatra et al. [78]. The authors also demonstrate a variety of image synthesis examples and applications while showing limitations of the work on very long frame sequences. Perez et al. [6] presented methods for texture flattening and seamless tiling using Poisson solver. This is applicable for instances where the flattening texture of the object could match with the destination color. Chen et al. [18] developed a component based compositing and view-aware compositing where a novel object is synthesized from multiple-source images that have different shape and viewpoints. The method provides innovative mean for creative designs of new objects and 3-D modeling.

3.1.1.4. 4. Image cloning. Perez et al. [6] demonstrated that their interpolation machinery using Poisson equation allows to create seamless cloning either by importing or mixing the gradients of source and target images. However, as described earlier, color bleeding limits its applicability to the areas where color change is not required. Leventhal et al. [79] created a technique called 'alpha interpolation', by extending Poisson image editing, to reduce the abrupt artifacts generated during mixed seamless cloning and luminance rescaling. A mean-value coordinate (MVC) based approach is introduced by Farbman et al. [80] for instant image cloning of large regions as well as video frames. The limitation of this method is that it could not be applied to every case wherever Poisson editing is used. Moreover, it works well when the texture of source boundary is similar to that of the target background. For seamless cloning, multi-grid solvers and diffusion solvers have been used by Jeschke et al. [81]. Bie et al. [82] proposed a new edit tool which provides the flexibility to preserve or conveniently manipulate the object appearance. Though it may result in inconsistent boundary regions when the region of interest is similar in color to the other regions. The authors [83] also developed an intent-aware image cloning method to suppress structure conflict between object and background. Like other methods, this work also fails when some parts of the object have similar appearance to the boundary region. To preserve the amount of color of the object inserted, recently, Henz et al. [73] used a Laplacian membrane modulation in seamless cloning. Their method ensures that the transition between the input images is seamless and unlike Poisson editing the excessive diffusion of background colors is not there. However, texture difference still remains a challenge to be addressed for seamless cloning.

3.1.1.5. 5. Image creation. Image composition from content specification is an emerging field of research. In contrast to other classes of compositing, the aim here is to choose suitable images based on the content specified and then blending or compositing operations are applied [84–86]. Lalonde et al. [52] proposed an automatic algorithm to improve object segmentation and blending. The authors also present a user interface for fast object insertion by querying an image-based object library. Although the method performs well, nonetheless several challenges like unrealistic appearance, shadows over objects, blending porous objects, etc., may result in failure of the system. *Sketch2Photo* [86] composes a realistic image composite by converting the simple freehand sketch and text labels of a scene provided by the user. Their method includes candidate image selection, filtering, blending, and optimization. However, there are many limitations of the system, and a careful consideration of factors like perspective difference between objects, occlusion between scene items, and relative scales of scene objects, is required for success of the method. In the similar context, Eitz et al. [87] used a database of millions of pictures for image retrieval and composition from a sketch interface. Recently, Wu et al. [19] presented a multi-scale image composition method based on semantic rationality of input images. Their method ensures semantic validity of the composite results, but it does not handle color bleeding and related blending artifacts completely.

3.1.1.6. 6. Image inpainting and completion. To fill the gaps in image regions *image inpainting* methods are used. In recent years, a variety of image inpainting and completion approaches have been introduced [88–90]. A comprehensive survey on image inpainting methods based on multi-resolution and Poisson editing is presented by Bugeau et al. [47]. Techniques like [54], [91], and [92] work by filling missing part of images whereas the methods proposed by Bertalmio et al. [89] and Dizdoroglu et al. [55] restore the defects in old photographs or damaged films. Barret et al. [93] presented texture inpainting by texture preservation and hole filling using object level granularity for real-time animation. In the same context, for filling missing region Hays and Efros [92] used semantic scene matching as well as local content matching while Shen et al. [64] employed Poisson equation for scene completion.

Further, for color image restoration and magnification inpainting Tschumperle and Deriche [94] used vector valued regularization and coherent anisotropic smoothing. Bornard et al. [54] applied constrained synthesis for missing data correction and image filling. Their method provides good results without user intervention for both still images as well as video sequences. Recently, Batool et al. [95] have incorporated an inpainting method to reduce facial wrinkles for retouching and beautification of facial skin. Their method uses two types of features viz. texture orientation field and Gabor filter responses, which are fused using Gaussian Mixture Models (GMM) and Markov random field (MRF) representations.

3.1.2. Overlapping

Image stitching is an effective way of creating an image with larger FOV from multiple images which have substantial overlapping part. Introduction of computer vision techniques have completely replaced the early methods of mosaic generation that used special cameras. These cameras were cumbersome and hardware intensive. In contrast, stitching techniques provide easier solution to align and mosaic images captured from any imaging equipment to generate high-quality image mosaics. As illustrated in Fig. 1, mosaicing of overlapping images involves three key steps based on which the stitching algorithms have been classified.

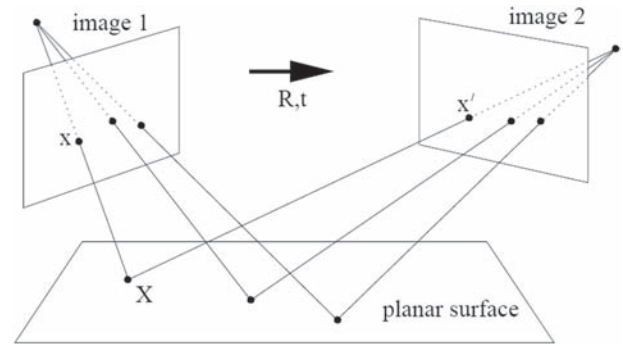


Fig. 7. Representation of planar homography [96].

3.1.2.1. 1. Image registration. Registration is an integral step of image stitching. The selection of a particular registration algorithm depends on the extent of image deformation, modality, and level of misalignment between a pair of images. To align the images, correspondence between two images is estimated and based on that the images are aligned on a common reference frame.

Some authors classify registration techniques based on geometric and photometric transformations [96,97]. Geometry refers to the shape whereas photometry encompasses the appearance (intensity of pixel) of an object.

i) Geometric registration. In this context, geometric registration refers to the estimation of certain transformation that aligns the two views of scene in a best possible way. Under a planar homography a point (x, y) is expressed as $(x, y, 1)$ and the points are mapped as shown in Fig. 7 . The expressions are given in the following way [96],

$$\mathbf{x}' = \mathbf{Hx} \tag{2}$$

$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \tag{3}$$

Here, H is a 3×3 homography matrix. To find the geometric correspondence between two images a homography matrix including planar transformations such as translation, rotation, scaling, projective, affine is usually calculated.

Different 2-D coordinate transformations are summarized in Table 1. These transformations are also called *parametric models* and each such model represents a specific camera motion. These models describe the coordinate transformation that map the image coordinate x to a new set of coodinates x', $\tilde{x}$ represents homogeneous coordinate. In Table 1, I is a (2×2) identity matrix, R is an orthogonal rotation matrix, s is an arbitrary scale factor, t is translation factor, A is an arbitrary (2×3) matrix, and $\tilde{\mathrm{H}}$ is a (3×3) matrix which is homogeneous. Here, the (2×3) matrices are extended to a (3×3) matrix using homogeneous coordinate transformation. More details on these transformation are presented in [98] and [99].

ii) Photometric registration. Different sources such as automatic camera adjustment and illumination variation due to change in ambient light may introduce photometric difference between images. A photometric model is presented in [96] which treats the three color channels (Red, Green, and Blue) independently. For each channel, a linear transformation consisting of two parameters α and β are modelled and the transformation is calculated as follows,

$$\begin{pmatrix} r_2 \\ g_2 \\ b_2 \end{pmatrix} = \begin{pmatrix} \alpha_r & 0 & 0 \\ 0 & \alpha_g & 0 \\ 0 & 0 & \alpha_b \end{pmatrix} \begin{pmatrix} r_1 \\ g_1 \\ b_1 \end{pmatrix} + \begin{pmatrix} \beta_r \\ \beta_g \\ \beta_b \end{pmatrix} \tag{4}$$

α and β are calculated by line-fit of intensity values of corresponding pixels using orthogonal regression. Bartoli [97] proposed a groupwise photometric transformation for modelling global lighting changes with comparatively less computational complexity.

On the basis of registration technique applied, the mosaicing approaches are also classified as direct method [100] and feature based method [34]. The former uses pixel information while latter performs feature detection and matching for the alignment of images as described in the following subsections.

iii) Direct methods. Direct approaches [97,100] use the pixel intensities to align the images. More importantly, these methods of registration attempt to minimize the intensity discrepancies between pixels by computing a transformation that optimizes the photometric consistency globally. These methods use minimization of intensity difference, correlation techniques, mutual information, etc. for image registration. A brief overview of these concepts is given below.

a) Minimization of intensity difference. Registration of images is sometimes [97,101] modelled as an iterative minimization problem that calculates the intensity difference between two images. Intuitively, for image translation one image is moved over the other till the difference between the overlapping region reduces to minimum value. It can be formulated as the sum of squared difference between two images [10],

$$E^2 = \sum_{x,y} \left[I_{t+1}(u,v) - I_t(x,y) \right]^2 \tag{5}$$

where $(u,v) = \mathrm{T}[(x,y)]$ and T is the transformation which calculates camera motion for mapping the coordinate system of image t to $t+1$. The aim here, is to minimize E^2 by calculating appropriate values of T. It is better suited for images with translation e.g. most of the video sequences have only translation.

b) Correlation based techniques. Normalized cross correlation (NCC) overcomes some of the problems of classical cross correlation. However, the remarkable property of phase correlation makes it better suited for registration as well as mosaicing. The main idea behind phase correlation is that, "Phase correlation algorithm is based upon the fact that the information pertaining to the displacement of two images resides in the phase of the cross power spectrum" [30]. Initially, 2-D Fourier transform (FT) is calculated for each image and then normalized cross power spectrum is estimated. The point of registration is the center of Dirac delta function obtained by taking the inverse FT of the phase difference between two images [102,31]. Phase correlation produces a distinct sharp peak at the point of overlap whereas in case of cross correlation the main peak does not always indicate the point of registration and the highest peak is not that distinct since it is surrounded by several other peaks [103]. The distinction between these two types is shown in Fig. 8[104]. Reddy and Chatterji [31] extend the idea of phase correlation to address translation, rotation, and scaling invariant image registration. Foroosh et al. [103] propose a subpixel registration technique based on estimation of polyphase components. Discrete cosine transform (DCT) based phase correlation has been used by [32,33] for mosaicing of images. Pandey and Pati [104] have extended the idea for blur invariant image mosaicing. Phase correlation methods are also better than iterative optimization method since the estimate of phase correlation method is global and it can work for translation upto 50% of image size.

c) Mutual information (MI) based methods. The similarity between two images is measured on the basis of amount of information shared. Higher the value of mutual information (MI) the better the alignment between the two images. MI based mosaicing methods are robust to occlusion and lighting variations [8,105,106]. However, these methods similar as NCC based methods, require larger area of overlap between images to be mosaiced. Further, these methods are computationally slower [8,105,106].

Direct methods consider all the information available in the image and hence, produce more accurate results. However, these methods are not that much robust to illumination variations. Further, the moving objects in the scene create problem during registration since all the pixels are considered.

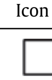
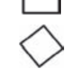
ii) Feature based methods. Feature based methods [28,34], on the other hand, rely on extracting some distinct or salient features from the images and matching them with other images to estimate an image-to-image mapping for registration. Feature based methods e.g. Scale invariant feature transform (SIFT) [35], have become more popular than their direct counterparts due to their robustness.

Different methods use different features like corner, point, line, gradient, difference-of-Gaussian (DOG), etc. The prominent methods in this category are Harris corner detection [107], SIFT [35], SURF [108], FAST [109], FREAK [110], etc. The methods which have been used extensively for mosaicing are described here. However, a detailed description and comparison of different features on mosaicing of images can be found in [111].

a) Harris corner detection. Harris corner detector [107] detects corners and edges based on local auto-correlation function. A windowed image patch is moved across the image and the change E_c is calculated as the difference between original and moved window multiplied with the window w at (x,y),

$$E_c = \sum_{x,y} w(x,y) \left[I(x+u, y+v) - I(x,y) \right]^2 \tag{6}$$

Table 1
2-D Coordinate transformation [98].

Parametric model	Transformation equation	Matrix	DoF	Preserves	Icon
Translation	$x' = x + t$	$[I\vert_t]_{2\times3}$	2	Orientation	
Rigid (Rotation + Translation)	$x' = Rx + t$	$[R\vert_t]_{2\times3}$	3	Lengths	
Similarity (Scaling + Rotation)	$x' = sRx + t$	$[sR\vert_t]_{2\times3}$	4	Angles	
Affine	$x' = A\tilde{x}$	$[A]_{2\times3}$	6	Parallelism	
Projective	$\tilde{x}' \sim \tilde{H}\tilde{x}$	$[\tilde{H}]_{3\times3}$	8	Straight lines	

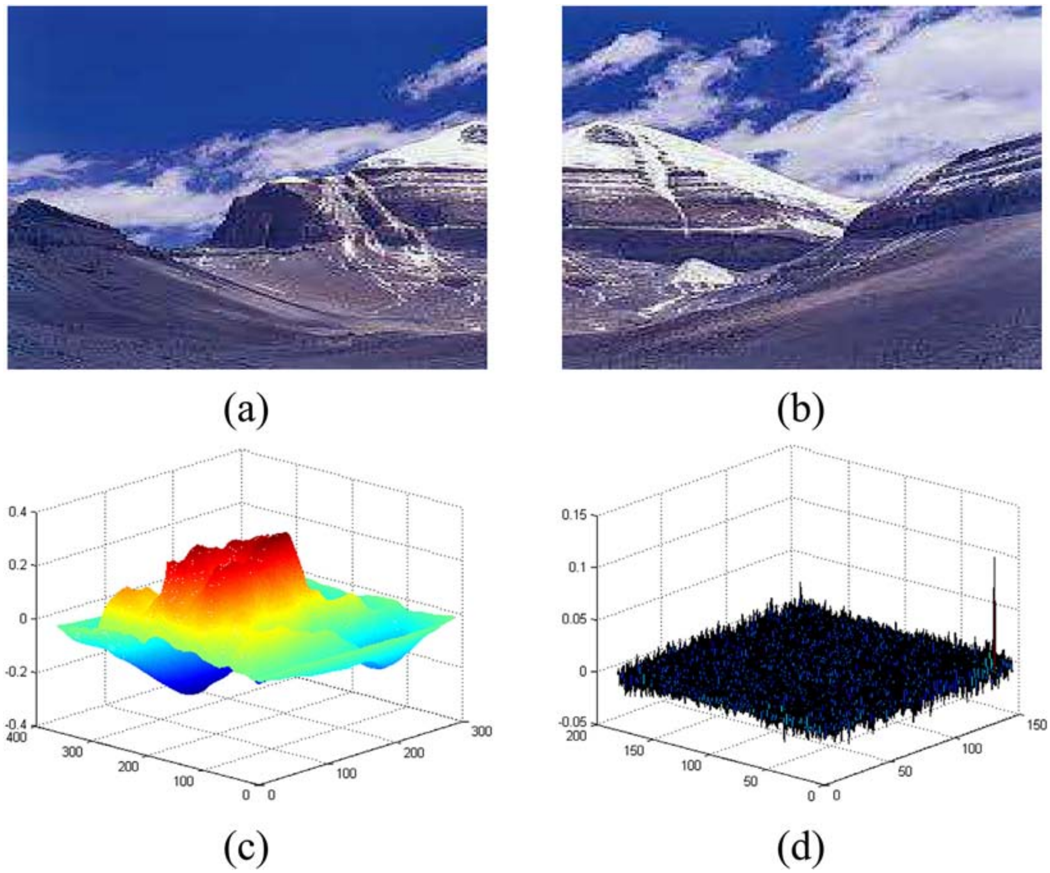


Fig. 8. Representation of cross correlation and phase correlation peaks. (a)–(b) Input images with displacement, (c) Cross correlation peak, (d) Phase correlation peak.

After Taylor series expansion E_c can be approximated as follows

$$E_c(u,v) \approx Au^2 + 2Cuv + Bv^2 \tag{7}$$

where A, B, and C are given as $A = \sum_{x,y} w(x,y)\, I_x^2(x,y)$, $B = \sum_{x,y} w(x,y)\, I_y^2(x,y)$, and $C = \sum_{x,y} w(x,y)\, I_x(x,y)\, I_y(x,y)$. The expression can be written in matrix form as,

$$E_c(u,v) = \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} A & C \\ C & B \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u & v \end{bmatrix}^T \tag{8}$$

M is the Harris matrix and the two eigen values λ_1 and λ_2 classify the regions and measure the quality of corner or edge. When $\lambda_1 \approx 0$ and $\lambda_2 \approx 0$ then at (x,y) there is no feature of interest. If $\lambda_1 \approx 0$ and $\lambda_2 \to$ *large* then an *edge* is located whereas if λ_1 and λ_2 are both large then a *corner* is detected. Rather than computing the eigen values, a measure of corner response function R is calculated to select the isolated corner pixels in the following way,

$$R = Det(M) - kT_r^2(M) \tag{9}$$

The determinant and trace of the matrix M are related to eigen values as $Det(M) = \lambda_1\lambda_2$ and $T_r(M) = \lambda_1 + \lambda_2$. Positive values of R indicate *corners*, negative values show *edge* regions, and small values of R represent *flat* regions. Fig. 9 shows the different regions as described earlier. A clear description of this figure is given in [107].

Once the corner points are detected, the two images are aligned based on the calculated geometric parameters and then warped over the compositing surface. Harris corner provides a simple yet accurate mean for feature based mosaicing.

b) Scale Invariant Feature Transform (SIFT). Scale invariant feature transform (SIFT) features [35] are highly distinct and invariant to scaling as well as rotation. These features are also robust to affine distortion, noise, and illumination changes. The major steps of computation of SIFT features are given below:

i) *Scale-space extrema detection* - To detect the invariant features difference-of-Gaussian (DOG) are used over different scales.

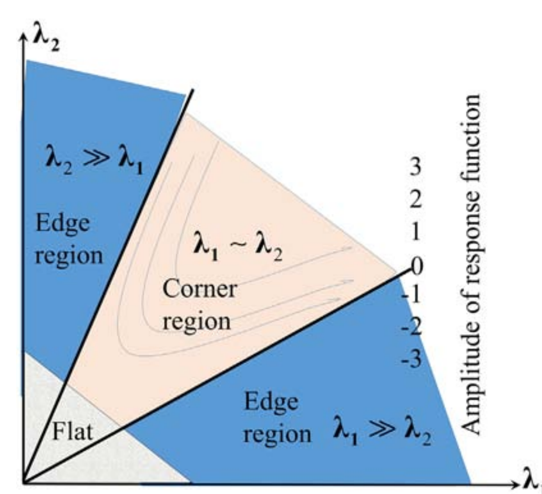


Fig. 9. Demonstration of different regions based on the values of response function *R*.

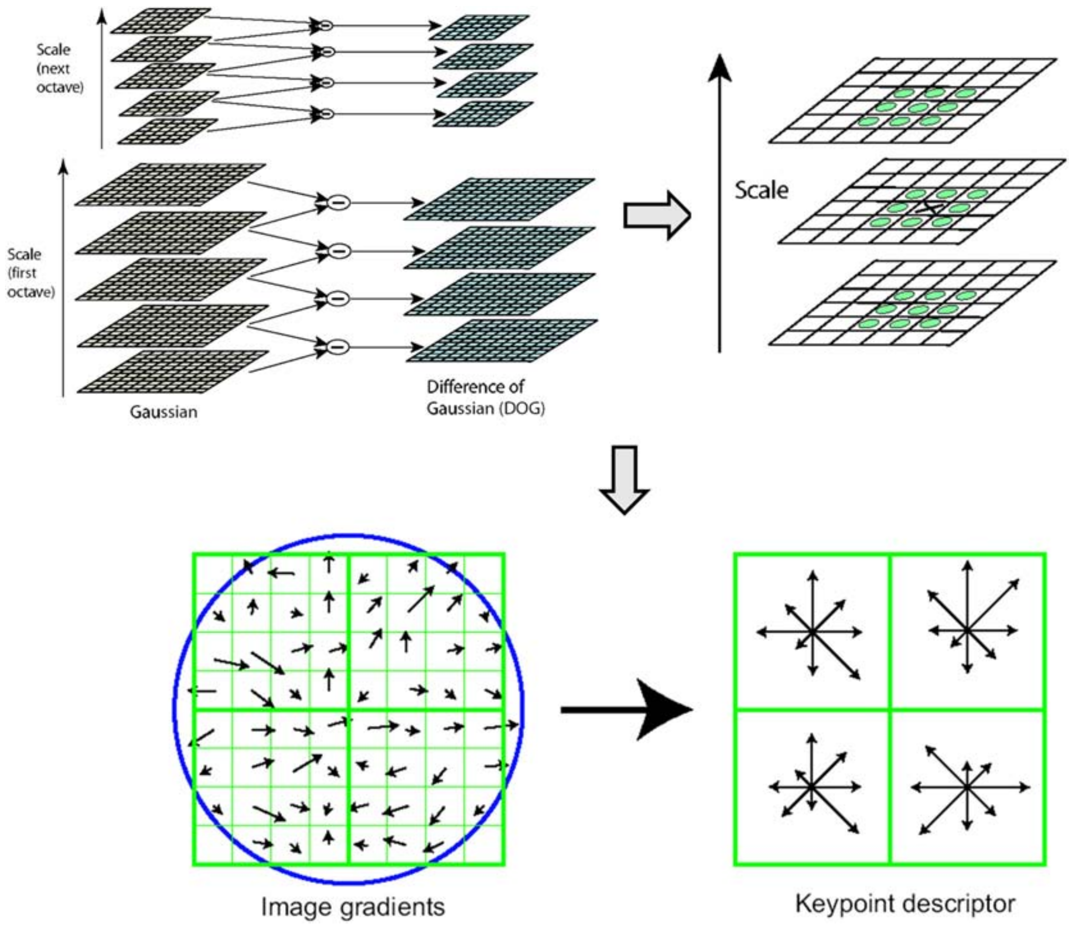


Fig. 10. Steps of feature detection using SIFT.

ii) *Localization of keypoints* - Out of all the feature points, only stable ones are selected while removing the low contrast error prone keypoints.
iii) *Orientation assignment* - The direction of highest peak of a gradient histogram formed from the gradient orientation of the local image, is assigned as the dominant direction or orientation to the keypoint.
iv) *Keypoint descriptor* - Each keypoint is represented by gradient magnitude and orientation in 16 × 16 region around it and finally, a vector consisting of 128 elements is computed as descriptor.

Fig. 10 describes the schematic of these steps for a better understanding [35]. Thus, the features are extracted and then matched for the upcoming stages of mosaicing.

c) Speeded Up Robust Features (SURF). Speeded up robust features (SURF) is a scale-space feature detector that significantly increases the matching speed [108]. SURF uses a Hessian matrix approximation for the detection of interest points. The Hessian matrix for an image I at point $X = (x, y)$ and scale σ is defined as follows,

$$H = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \tag{10}$$

L_{xx}, L_{yy}, and L_{xy} are the responses of Laplacian-of-Gaussian (LOG) filter. Practically, the Gaussian is discretized and the approximation is denoted by D_{xx}, D_{yy}, and D_{xy}. The determinant of H is given as,

$$Det(H) = D_{xx}D_{yy} - (wD_{xy})^2 \tag{11}$$

w is the relative weight to balance the expression. The determinant represents the expression blob response at location X which is stored in different scales. These scales come from octaves as represented in Fig. 11. The interest points are localised by a non-maximum

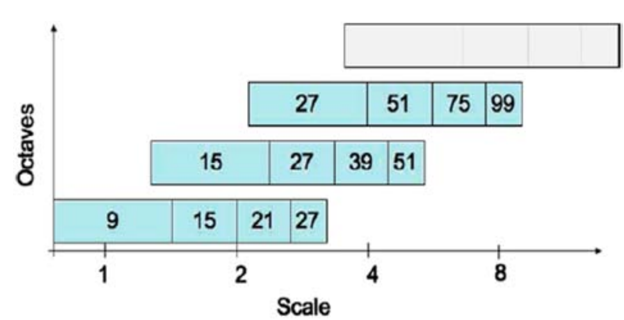


Fig. 11. Representation of octaves and scale. (Adapted from [108].)

suppression within a 3 × 3 × 3 neighbourhood. A point X is selected as an interest point if the $Det(H)$ has higher value than its 8 neighbours in that scale and also the 3 × 3 neighbours in the successive scales. For assigning the orientation, a circular region around the feature point is considered, and Haar-wavelet responses are calculated. A window of size 60° is considered and the responses within it are approximated as dominant orientation.

To construct a descriptor within a squared region around the interest point, it is assigned the orientation calculated in the previous step. A descriptor vector of length 64 is obtained by taking the absolute values of wavelet responses. The features are matched and outliers are eliminated for calculation of homography matrix. Based on this matrix, the images are warped and then stitched to construct the mosaic.

Feature based methods are robust to camera rotation, zoom, and illumination variations. Additionally, they handle moving objects in the scene robustly by detection and removal of outliers (i.e. erroneous points in displacement vector that are not consistent [20]). Thus, feature based methods produce better results without the need of larger overlapping area for mosaicing. In spite of all that, these methods fail to perform well when the image regions either do not have enough texture or are too textured.

3.1.2.2. 2. Image re-projection. Once the images are registered with respect to each other, next step is to decide how to generate the final stitched image. To estimate the final projection model, the aligned images obtained after registration are transformed onto a larger surface which is called a *re-projection manifold* or a compositing frame. The re-projection manifold is chosen depending on the way the user wants to represent the final mosaic image and also based on the camera motion involved. For instance, if only a few images are to be mosaiced then the resulting composite image is a flat panorama involving projective transform i.e. straight lines remain straight in the mosaic. However, for large FOV images, if multiple images are stitched on a flat surface then it looks distorted. In such cases, the usual practice is to use either a cylindrical or spherical projection to keep the appearance undistorted.

Several factors need to be considered before choosing a compositing surface. These factors are: a) View selection, b) Coordinate transformation, and c) Sampling issues. View selection is needed to determine the central part of the scene to be kept in the middle of the mosaic as reference view for rest of the images. After selection of view, the mapping between the input and output pixels is calculated. For flat mosaics, simple homography is used whereas for cylindrical or spherical surfaces each pixel is converted into a viewing ray which is then mapped back into each image according to the projection equation [14,98]. Sampling issues are important to avoid aliasing in the final composite. Aliasing occurs when the output mosaic has lower resolution than the input images and it can be avoided by pre-filtering the images. Further, higher resolution mosaics can be produced from lower resolution images using an approach called *super-resolution* [96].

In general, there are three types of re-projection manifold as described below. These manifold are shown in Fig. 12.

i) Planar. For simple camera motion such as translation, planar projection is suitable and commonly used compositing surface. The images are re-projected on the surface based on the calculated homography matrix. Planar projection preserves the straight lines in the image, but it is not suitable for wide FOV mosaics.

ii) Non-planar. The most important use of mosaicing techniques is the generation of wide FOV panoramas from a single camera rotating about its axis in different directions. A cylindrical surface is used for re-projection of such image sequences. In this case, the images rendered do not suffer from the distortion that occurs in case of planar projection. Here, the transformation maps the polar coordinates to rectangular image coordinates. Spherical projection is also an option for non-planar projection, however, due to lack of satisfactory mapping of different coordinates and singularities, spherical projection is not used much.

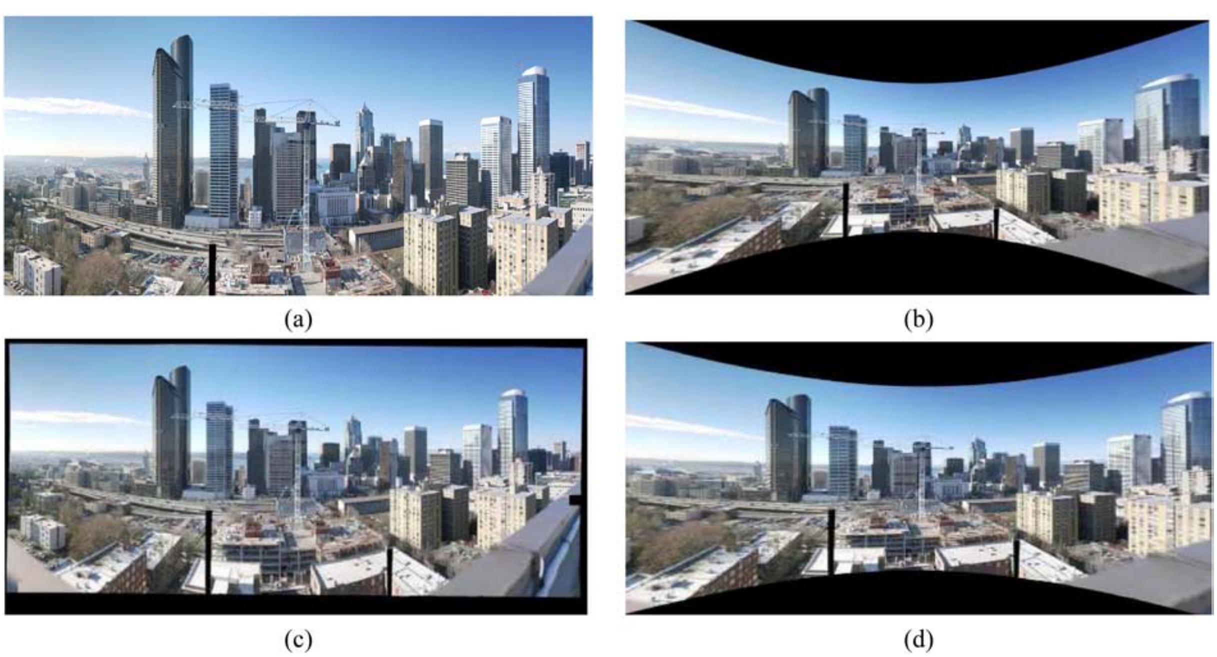


Fig. 12. Demonstration of different re-projection manifold. (a) Original image, (b) Projective manifold, (c) Cylindrical manifold, (d) Adaptive manifold. Both, projective and cylindrical manifold increase the FOV, but with distorted peripheral region while adaptive manifold preserves it [112].

iii) Adaptive. Over the years, rather than using a predefined projection manifold some researchers [113,114] use an adaptive manifold. Peleg et al. [113] used an adaptive compositing manifold based on the calculation of optical flow. The approach is applicable to videos or highly dense images. Lin et al. [114] employed affine transform with spatial variation for stitching of images having parallax and motion. It provides better flexibility, but at the cost of distortion in the final mosaic. Recently, a stitching method is proposed with automatic warp using local homography and global similarity transformation to mitigate the perspective distortion as well as visible parallax [115] during image stitching.

However, geometric and photometric errors due to registration inaccuracies as well as other factors like illumination variation, exposure difference, color imbalance etc. often result in discontinuities between the images in the overlapping region. This results in creation of spurious seam in the mosaic. Therefore, blending algorithms are needed after warping of images for seam smoothing and reducing the visible artifacts.

3.1.2.3. 3. Image blending. Once the input images are projected onto the re-projection manifold, the color of each pixel in the final stitched image needs to be decided. The exposure differences and the errors generated after registration as well as warping are reduced using an appropriate blending technique. It is the most important step in stitching for generation of seamless mosaics, and a lot of work has been done in this area. As a result, various types of blending algorithms exist. The mosaicing algorithms are classified into three categories based on the blending strategy they apply for removing the visible discontinuities.

i) Transition smoothing method (TS). Transition smoothing (TS) methods try to mitigate the visible difference in the overlapping/transition region between two images, by replacing the pixels in the transition region with the weighted average of the contributing images. Alpha blending [116] is the most common TS method. In literature, different TS methods based on Pyramid [38], wavelet [117], gradient-domain techniques [39], etc. have been proposed.

ii) Optimal seam finding method (OS). Contrary to TS methods, optimal seam finding (OS) techniques estimate a seam in the overlapping region which produces least visible discrepancies between images. Methods such as dynamic programming [16,118], graph-cut [43,119], watershed [26], etc. are some of the popular OS methods.

iii) Hybrid blending (HB). As the name implies, this particular class of blending combines the blending approaches from the two groups of blending explained earlier i.e. TS and OS. Thus, it takes the advantage of both the methods. Research work like [37,43] and [45] describe hybrid blending methods.

3.2. Based on the blending strategy adopted

When the images are mosaiced, there is a creation of seam along the image boundary. Image blending alleviates these seams by employing adequate blending strategies. It is the most essential step for a visually pleasant mosaic generation, since it reduces the visual discontinuities often visible between image regions. Most of the blending algorithms have following major concerns:

(1) Minimization of the illumination variation or exposure difference between images.
(2) Detection of appropriate seam to mitigate the visible difference around it.
(3) Smoothing the seam to ensure seamless transition between images.

Based on different category of images, the related blending issues vary considerably. For example, the non-uniform illumination and exposure problems common in underwater images are not much pronounced in case of aerial images. Therefore, blending approaches have got increased attention over the last few decades due to the accelerated use of blending methods in all sorts of editing and mosaicing related operations. As a consequence, a large number of blending approaches have been developed and it is, therefore, an important attribute to be considered while classifying the mosaicing algorithms. The most relevant approaches for blending of images have been categorized in three groups as described earlier i.e TS, OS, and HB. This classification is to enable the researchers to recognise and choose the most suitable blending algorithm for a particular problem in hand.

3.2.1. Transition smoothing method (TS)

The basic concept of blending was presented decades ago in 1975 by Milgram [36] for smoothing of two horizontally registered images and this resulted in the development of subsequent blending approaches. Blending techniques based on transition smoothing (TS) attempt to reduce the visual difference in the overlapping region between two images by smoothing. One of the popular TS method is *alpha blending* [120] where the images are combined with the masks weighted by a factor α and then finally combined to generate the mosaic. *Feathering* [121] is also used for such smoothing operations to reduce sharp edges. Peleg [122] introduced a seam elimination function (SEF) for smoothing the seam not only between two images but also for any arbitrary number of aerial images not necessarily overlapping with each other.

Pyramid blending [38] has been used for blending the image features at different resolution levels. Both, low-frequency as well as high-frequency details are separated and treated independently by employing smoothing functions. Burt and Adelson [38] used pyramid for various applications including image compositing. Their method reduces the visibility of seams in the mosaic, however, in the presence of registration error the method results in ghosting and double contouring. Sunkavalli et al. [66] used pyramid blending for appearance harmonization to transfer texture and style whereas Brown and Lowe [28] incorporated it for automatic panorama stitching. Recently, Pandey and Pati [123] used the concept of pyramid blending with Savitzky-Golay (S-G) filter for non-overlapping image mosaicing. The authors extended the idea using saliency and 2-D exponentially weighted Savitzky-Golay (2-D EWS-G) filter for compositing multimedia images [124]. The method of Burt and Adelson [38] was further extended in wavelet domain by Hsu and Wu [117] with similar results as [38].

Gradient-domain methods have evolved as an important tool for seamless blending of images. In this context, Perez et al. [6] introduced a generic interpolation machinery for seamless cloning. After alpha blending and pyramid based methods, this is the first blending approach in gradient domain which utilizes gradient importing, gradient mixing, texture flattening, and illumination/color changes. Although the focus of this work was mainly on image editing and compositing, many variants of it emerged over the years that are used for image stitching as well. As discussed in Section 3.1.1, the variants of Poisson equation find application in image compression [63], image completion [64], and image inpainting [89]. For seamless image stitching, Levin et al. [39] introduced a gradient domain approach where they optimize several cost functions in order to mitigate the seam artifacts. Agarwala et al. [43] introduced a blending method that combines graph-cut optimization for optimal seam finding and gradient domain fusion for removing the remaining visual artifacts from the images. However, the work required user guidance for selection of image regions and thus not suitable for automatic generation of image composites. The authors also presented a quadtree based approach for the betterment of gradient domain compositing. A multi-spline representation associated Poisson blending and gradient domain compositing is used by Szeliski et al. [125]. Gradient domain methods for blending are also popular in underwater image mosaicing. Gu and Rzhanov [40] presented a blending technique that uses gradient domain fusion of boundary pixels only. Gradient domain TS method has been widely used for compositing of images. Jia et al. [17] used Poisson editing in conjunction with alpha blending whereas Yang et al. [70] applied variational model considering gradient constraint followed by multi-resolution blending. Lalonde et al. [52], Hays et al. [92], Ballester et al. [91], Georgieve et al. [68], Dizdaroglu et al. [126], and Bie et al. [82] are among others who contributed towards gradient based blending for different compositing operations. The problem often encountered while working extensively in gradient domain is the computational burden.

3.2.2. Optimal seam finding method (OS)

The aim of optimal seam (OS) finding algorithms is to estimate an optimal seam in the overlapping area where minimum visible discrepancies occurs between the images. This seam takes into account the content of both the images and, therefore, handles the problems like parallax or moving object in the scene.

Milgram [36] proposed a photomosaicing method for registering and the best seam finding between images. Thereafter, the intensity difference between the images is minimized by smoothing the seam. To reduce the induced intensity difference, the author improved the method for gray scale registration as well as best seam selection using dynamic programming. Davis [127] addressed the problem of moving objects by developing a global registration method and a segmentation operator. The blurring artifacts due to moving objects are minimized by ensuring that the segmented regions are filled with the sampled pixels belonging to any one of the source images. However, the other issues like exposure or vignetting are not addressed in this work. For fixing panoramic photography related problems, Uyttendaele et al. [121] presented novel algorithms. Their method is mainly to remove the ghosting effects due to moving objects and to adjust the exposure in the mosaiced image. The exposure adjustment, however, does not smooth the region completely and noticeable seams are visible in some cases. A compositing framework called *digital photomontage* was introduced by Agarwala et al. [43] for creating a single composite image that better conveys the user's perception. The authors employ graph cut optimization for seam selection and gradient domain fusion for removing the visual discrepancies that remains after merging the two images. Their algorithm offers seamless results for a variety of applications with the help of user interaction or guidance. Eden et al. [119] presented a two-step graph cut technique to smoothly stitch the images even in the presence of exposure difference, scene motion, and misregistration errors. Their method generates high dynamic range (HDR) panoramic stitching. Rav-Acha et al. [128] proposed a minimal aspect distortion (MAD) method for mosaicing of images that minimizes the geometric distortion using motion and depth computation in panoramic images. However, ambiguity and occlusions make it impossible to compute the depth and hinder the process. To reduce the memory and computation burden of Dijkstra's algorithm for seam finding, a graph cut and watershed method was proposed by Gracias et al. [26]. The authors use graph cuts and provide globally optimal solution for underwater image blending. In the similar context, Gu and Rzhanov [40] proposed an optimal seam selection technique and apply a gradient domain fusion method around the selected boundary to deal with the inhomogeneous illumination problem often occurring in underwater images. Summa et al. [129] proposed a method called *Panoramic Weaving* for creation of global seam for boundaries of panorama. Their method is fast and memory requirement is low as compared to other techniques. The image whose boundary is covered by another image is not considered in the work. Philip et al. [49] extended the work of *Panorama Weaving* by introducing a scalable version of it to handle arbitrary panorama size while requiring limited memory. A color correction and color blending method is developed by Yao and Li [130] to reduce the photometric differences while minimizing the processing delays in mobile panoramas.

3.2.3. Hybrid blending (HB)

This class of blending methods does not have any new blending technique, but a combination of TS and OS methods. The hybrid approaches initially calculate an optimal seam between images and then apply an appropriate TS method around the seam. This type of combination helps to overcome the difficulties like ghosting and double contouring occurring in TS methods and illumination difference related artifacts in OS methods. As a result, hybrid methods are quite successful in generating seamless image mosaics.

Milgram [118] proposed a method for optimal seam selection in row-wise fashion and later applied a weighted average around the seam in the transition region to reduce the visual differences. The method was mainly for satellite images and confined to gray scale images registered horizontally. Agarwala et al. [43] developed a hybrid method using graph cut for optimal seam finding and gradient domain fusion for transition smoothing. Their method effectively compensates exposure variations and retains color coherency of each color channel. However, the method is mainly intended for compositing of images with user involvement. In the similar context, Eden et al. [119] used the advantages of both graph cut and gradient domain for creating full view panoramic images with HDR. Also, the authors visualised the final HDR images using a tone mapping algorithm. Gu and Rzhanov [40] performed underwater image blending using similar hybrid approaches. Although their method does not handle the ghosting artifacts around image boundaries quite convincingly, it is an important approach in underwater mosaicing literature. Recently, Prados et al. [29] addressed the underwater blending issues using graph cut and gradient blending method. A mosaicing approach is proposed by Mills and Dudek [131] that comprises of graph cut using Dijkstra's algorithm and multiresolution splining. However, this method suffers from exposure difference, ghosting, and double contouring due to the contributing methods. Likewise, Yang et al. [70] and Eitz et al. [87] used hybrid methods for image editing/compositing while Bugeau et al. [47] used such combination for image inpainting applications. Xiong and Pulli [16] utilized hybrid blending for generation of high-quality panorama on mobile phones. Liang et al. [132] employed hybrid method consisting of histogram normalization and weighted average for mosaicing of document images. Currently, a combination of gradient domain blending with optimized boundary was used by Chen et al. [45] for video compositing and editing applications.

Hybrid methods provide better results as compared to the individual techniques of blending. However, the computational burden increases when two or more methods are combined for blending.

3.3. Based on the motion of frame

Mosaicing methods can also be classified based upon the motion of the input image frames. If the input images of a scene considered for mosaicing are still pictures, captured from any handheld camera then the mosaics are called *static mosaics*. On the other hand, if the input images are taken from a video clip representing a scene, structure, or situation then the mosaic created are called *dynamosaics*.

3.4. Based on the area of application

Different applications require different modality of images. The application area of mosaicing is vast. The classification based on various applications are demonstrated through a flow chart in Fig. 6.

The mosaicing algorithms are used for a number of applications like panoramic, medical, underwater, aerial/satellite, face recognition, biometric, compositing and its variant applications, and so on.

3.4.1. Panorama creation

This group of blending algorithms addresses the aligning and stitching of smaller individual images to generate a single image with larger FOV without compromising the resolution of the images [130,133]. It is used for capturing a wide angle view of a tall building or sceneries [134]. Panoramas are rich in visual information and there are many applications which require wide angle view like street views [23,135], mobile panoramas [130,16], multi-spectral 3-D field panorama [136], just to name a few.

3.4.2. Aerial

These approaches fuse terrestrial and aerial images for creating an entire view of the scene under consideration. It is required for the study of environmental monitoring and protection [137]. Photomosaic generation of earth's surface [36], different topographic regions [118], mosaicing of images captured under varying environmental condition [122], and production of seamless satellite mosaics [22], are also crucial areas of application.

3.4.3. Medical applications

In medical applications, a single camera inserted inside a patient's body cannot capture the whole view of the organs at a time [138]. However, the images with different viewing angles can be mosaiced to generate a complete view of the patient's organ in 2-D for clear visualization and monitoring as required during the diagnosis of abnormalities. Creation of microanatomical structures [137], mosaicing of bladder images for detecting lesion and cancer [3,105], and mosaicing of confocal microscope images [4] are the recent mosaicing methods used in biological studies.

3.4.4. Document mosaicing

Document mosaicing is a special case of mosaicing for camera captured document image stitching. Document images suffer form several problems such as resolution, perspective and curvature distortion. Further, full view of these images are often difficult to obtain in a single scan. Stitching the smaller patches of image together can generate full view of the document with apparent ease. Researchers [132,139,140] have provided solution to these issues for generation of distortion free mosaics. Zappala et al. [139] presented a mosaicing technique for documents as an alternative to flat-bed scanner. Their method is quick, robust, and fully automatic. However, curved surfaces were not addressed in the method. Curved document mosaicing from video frames was introduced by Iketani et. al. [140]. Liang et al. [132] proposed a technique to produce high resolution document mosaics from smaller images with zoom and poses using Hough-transform like voting method to resolve the scaling and translation.

3.4.5. Underwater mosaicing

Underwater optical mapping is required for seafloor exploration as well as other scientific applications [29]. Mosaicing of underwater images is a challenging task with higher complexity as compared to their terrestrial counterparts due to constrained acquisition of images in underwater medium. Different problems of underwater mosaic generation or 3-D reconstruction have been explored over the years [26,40] and the problem of challenging underwater media has been addressed up to some extent [29,41]. However, there are many open challenges in underwater mosaicing which need research attention.

3.4.6. Biometric

Mosaicing plays very important role in biometric systems too. 2-D face recognition is a critical research problem in computer vision. The existing approaches are sensitive to illumination changes, pose variation and facial expressions. 2-D face mosaicing [8] provides a competent solution for characterising an individual's face in 2-D plane without requiring 3-D structure information and avoids computational complexity associated with 3-D facial imaging. It also removes the need to store templates of different poses of an individual. Similar to face, Choi et al. [9] propose a novel fingerprint sensing device and a mosaicing method for compositing multiple-view fingerprint images.

3.4.7. Image compositing

Recently, image compositing has gained wide attention in the vision and graphics community [73,124]. Some region or object of one image is merged over another image to create a completely new scene without noticeable artifacts at the border of the two images [141]. Image composition [50,63,69] is a key component in image editing, advertising, animation, and visual effects. However, the seamless creation of composites still has number of problems that need to be solved.

4. Discussion and comparison of algorithms

In the last section, a detailed classification of different mosaicing methods and the underlying concepts have been explained. Here, a comparative analysis of these methods is presented to provide a clearer view of mosaicing algorithms.

Table 2 illustrates a summary of image stitching methodologies with consideration of their main concepts, blending techniques, advantages, shortcomings, and the specific area of application.

Table 3 demonstrates a list of compositing algorithms popular in the literature of computer vision, graphics, and image processing. The methods have been analysed depending upon the methodologies employed for compositing, specific class of compositing, blending methods applied, advantages, and shortcomings.

4.1. Selection of suitable registration method

Effort has been devoted to explore the different registration methods for image stitching. Most of the geometric deformations are taken care by the registration techniques while photometric inconsistencies are handled by blending methods. As explained earlier, both direct as well as feature based methods have their own advantages and drawbacks. For the user, it is often confusing, to select any one of these methods for a particular application. Table 4 provides a quick review of these two classes for making the selection easier for the user.

With the advancement of technology and the requirement of user applications, a combination of these methods have become a popular choice. Feature based methods provide coarse registration while direct methods such as MI based techniques make the alignment more accurate by fine registration.

4.2. Selection of suitable blending method

Blending is the most important step of both stitching and compositing for generation of seamless and high quality mosaics. Over the years, it has grown extensively. As a result, numerous blending techniques have come into existence. Selection of blending methods

Table 2
Analysis of different mosaicing methods.

App.	BT	Ref./Yr.	Methodology	Advantages	Shortcomings
Aerial	TS	[36] 1975	Row-wise seam searching.	First attempt towards photomosaicing.	Works for only two horizontally registered images.
		[22] 2012	Multiple-image blending based on energy function optimization.	Panoramic, aerial, biomedical	NS
	HB	[118] 1977	Gray scale registration and dynamic programming.	Adaptive method for blending.	NS
	OS	[122] 1981	Seam-eliminating function and relaxation algorithm.	Any arbitrary number or shape of image parts.	Vignetting causes illumination artifacts.
Biometric	TS	[8] 2007	Blending of side profile images with the frontal image to generate composite face image.	Face mosaicing	A frontal face as reference is always required.
		[9] 2010	Touchless fingerprint sensing device and mosaicing the captured images	Fingerprint mosaicing	No matching method optimized for touchless images.
Document	TS	[139] 1999	Multiple overlapping document images are stitched together seamlessly to form a high resolution composite	Document mosaicing	Mosaicing is strictly pair-wise and no means to register non-consecutive images.
	HB	[132] 2009	Document mosaicing using texture flow information and Hough transform-like voting.	For images with perspective distortion, displacement, and small overlapping area.	Very time consuming.
Underwater	TS	[41] 2013	A novel blending pipeline designed to cope with underwater issues.	Diminishes photometric irregularities.	Mainly for forward-looking sonar (FLS) images
	OS	[26] 2009	Watersheds and graph cuts.	Efficient mosaic creation without user intervention, reduced computational cost.	For underwater images.
	HB	[40] 2006	Blending using graph-cut and gradient domain technique.	Reduces ghosting and lighting difference.	Some blending artifacts require further investigation.
		[29] 2012	Graph-cut in gradient domain for underwater gigamosaicing.	Adequate seam finding for different exposure images.	Parallax, illumination and other issues degrade mosaic quality.
Medical	OS	[105] 2008	Mutual information and stochastic gradient optimization for registration.	Bladder cancer diagnosis using endoscopic mosaics.	Image quality and data variability affect the process.
	TS	[3] 2010	Mosaicing of cystoscopic sequences of internal bladder walls using perspective geometric transformations.	Detection and visualization of bladder lesions using fast and automatic algorithm.	Endoscope orientation causes severe perspective distortion for colon and esophagus.
		[138] 2011	Increasing FOV of microscopic images using global and local registration.	Addresses cumulative image registration errors and scene deformation.	NS
		[22] 2012	Multiple-image blending model based on optimization of energy function.	Image stitching (Panoramic, aerial, biomedical).	NS
		[4] 2012	Multiresolution optimization for blending coefficient estimation by solving quadratic programming.	Confocal microscope image mosaicing.	Confocal images suffer from intensity loss due to scattering and absorption of fluorescence.
Panoramic	TS	[5] 1997	Full view panorama and environment maps generation using a set of transforms.	Fast and robust, increases accuracy and flexibility.	Requires deghosting, block adjustment, and other algorithms for good quality.
		[28] 2003	Fully automatic panorama generation based on invariant local features and probabilistic model.	Insensitive to scale, order, illumination, and orientation of input images.	NS
		[39] 2004	Optimization of different cost functions for Gradient-domain Image STitching (GIST).	Reduces inconsistencies due to illumination, seam, and edge duplication.	To handle large datasets in gradient domain it requires computational resources.
		[15] 2004	Minimization of a blending energy function with two variation terms.	Blending around circular boundary.	Perceptual quality of the mosaic is not considered.
		[142] 2004	Colour correction of panoramic images based on opto-electronic conversion function (OECF).	Corrects the exposure, white point, and vignetting in mosaics.	Camera's functions need to be modelled which may vary from one to another.
		[13] 2007	Use of invariant local features and a probabilistic model to recognize and stitch unordered images automatically.	Insensitive to camera zoom, order, illumination, noise, and orientation of images.	Radial distortion parameters are required to be included for good quality mosaics.
	OS	[127] 1998	Global registration using Mellin transform and optimal seam finding using Dijkstra's algorithm.	Addresses mosaics with moving objects in the scene.	Other factors causing discontinuities are not considered.

(*continued on next page*)

Table 2 (*continued*)

App.	BT	Ref./Yr.	Methodology	Advantages	Shortcomings
		[119] 2006	Two-step graph-cut procedure to define the object position and to fill in the dynamic range for photomosaicing.	Reduces exposure difference, scene motion, and misregistration error.	NS
		[128] 2008	A minimal aspect distortion (MAD) mosaicing to minimize the geometrical distortions of long panoramic images.	Rendering mosaics from thousands of frames using a hand-held camera.	Ambiguity and occlusions affect depth computation.
		[129] 2012	Produces seams with lower energy than the competing global techniques.	First interactive technique for the exploration of the seam solution space.	An image whose boundary is completely enclosed by another image is considered invalid.
		[49] 2015	Seam computation for gigapixel sized panoramas using parallel, out-of-core technique.	Method is fast, less memory requirement, and scalable.	Lacks interactive editing.
	HB	[23] 2006	Panorama generation using Markov random field (MRF) optimization and interactive refinement.	Allows user interaction to describe desirable properties of multi-view panorama.	Works well for urban streets, but not much effective for other scenes.
		[16] 2010	High-quality mosaics for mobile phones using dynamic programming and linear blending.	Less memory requirement and faster than graph-cut.	Poisson blending needs more computation and memory.
		[27] 2012	Correcting panoramas using seam-editing tool and content-aware snapping tool for local image warping	Panoramic mosaicing, photo-editing, interactive editing tool	Jittering during warping.
Compositing	TS	[38] 1983	Seam smoothing using Spline.	Works well even for irregular shape components.	Double contouring and ghosting in case of misalignment.
		[117] 1996	Extended the idea of Burt and Adelson in wavelet subspaces.	1-D and 2-D signal mosaic.	Similar results with higher computational cost.
		[143] 2006	Seamless stitching by minimizing false edges, optimization of gradient image,	Panoramic stitching, object insertion.	Computationally expensive.
	OS	[6] 2003	Seamless editing based on solving Poisson equations.	Image compositing/editing/cloning.	Color bleeding.
	HB	[43] 2004	Graph-cut optimization and Gradient-domain fusion.	Compositing, panoramic stitching, relighting, time-lapse mosaics.	Requires user guidance for interest image region.
		[17] 2006	Optimized boundary condition based on objective function for Poisson image editing.	Reduces intensity difference along the boundary between images in the composite.	User intervention required, color bleeding.
		[70] 2009	Random walk, Poisson editing, and multiresolution pyramid blending.	Image compositing without user supplied mask.	Fails when the source and destination images are completely different.
		[47] 2010	Comprehensive framework for image inpainting.	Image editing, resizing.	Larger patch size and inappropriate mask location results in poor images.
		[27] 2012	Seam-editing tool and content-aware local image warping.	An interactive editing tool for correcting panorama and photo-editing.	Jittering during warping.

App.-Applications, BT-Blending technique, Ref./Yr.-Reference/Year, TS-Transition smoothing, OS-Optimal seam finding, HB-Hybrid blending, NS-Not specified

mainly depends on three factors: 1) type of images to be blended, 2) inconsistencies involved, 3) user's intention.

The blending methods for medical images or compositing may not be suitable for underwater images. Moreover, the objects in the scene, texture, and color also need to be taken care while blending the images. Similarly, if the images have illumination or exposure differences then just feathering or smoothing the seam may not be sufficient and gradient domain methods which handle such differences are required for efficient blending. Further, if the user wants to reduce the illumination difference without changing the object color in compositing, then a combination of blending methods needs to be provided. Table 5 describes different blending techniques and their combinations.

4.3. Challenges in different areas for possible future research

The challenges of image mosaicing differ with varying areas of application. Each area has its own set of challenges that needs to be tackled tactfully. For *panoramic* images or sceneries, the main hurdles during mosaicing are accurate alignment, illumination difference, moving objects in the scene, camera motion, shadows etc. These challenges have been addressed and solved by the researchers up to some extent. However, the level of complexity of registration, warping, and blending increases with the increase in number of images used for stitching.

Underwater mosaicing is one of the most challenging areas where problems arise from the beginning (i.e. image acquisition) to the end (i.e. final mosaic generation). In contrast to other areas of mosaicing, underwater images suffer a lot due to poor visibility. Underwater medium causes scattering, reflection, and refraction of the light rays due to which the proper capturing of images becomes quite difficult. Moreover, moving objects like fish, algae, and other plankton make the process even harder. Furthermore, the artificial light source used to capture the images introduces noise and vignetting effect in the captured images. All the above mentioned factors result in low-contrast images that need to be enhanced before registration.

Table 3
Analysis of different compositing methods.

CT	SC	Ref./yr.	Computational approach	Applications	BT	Editing involved
Matting	DIM	[120] 1984	Compositing based on α matte channel calculation.	Compositing multiple images	TS	Compositing, handling darkening attenuation and opaqueness.
		[56] 2001	Matting based on Bayesian approach for blue screen, difference, and natural matting.	Image compositing	TS	Matting for different background.
	BSM	[59] 1996	A multi-background technique for blue screen matting using triangulation solution.	Compositing	TS	Blue spill, backing impurities, backing shadows.
	NM	[57] 2000	Estimating to produce the extent of two colors in the color of the boundary.	Image extraction	TS	Transporting an object from one image to another.
		[58] 2001	Pixel color calculation and K-nearest neighbour classifier.	Image segmentation	-	Segmentation of subjects and moving image sequences.
		[144] 2008	Calculation of a cost function by eliminating foreground and background colors to find .	Image and video editing	-	Image compositing, shadow matting.
	DM	[60] 1999	Calculation of color difference between input and background frame, and refinement of the probability map anisotropic diffusion.	Background replacement	TS	Real-time implementation for video editing.
	PM	[61] 2004	Estimation of matte gradient from input image and reconstructing the matte using Poisson equation.	Multi-background, De-fogging	TS	Multiple background compositing, De-fogging using boosting brush.
	SM	[145] 2008	Eigen vectors of the matting Laplacian are used to compute fuzzy matting component.	Compositing	TS	Spectral image segmentation.
	VM	[146] 2005	Data-rich imaging and novel optimization method for defocus matting.	Video matting	-	Artifacts and noise removal, video filtering, artificial depth of field.
	CM	[147] 2007	Integration of matting and compositing into a single optimization process.	Image editing	-	Image manipulation, foreground zooming, scaled compositing.
Image and texture synthesis	TTS	[75] 1999	Markov random field (MRF) and conditional distribution estimation by querying sample image.	Texture synthesis	-	Preserving local image structures, foreground removal, motion synthesis such as ocean waves, rolling clouds, burning fire.
		[79] 2006	Alpha interpolation and luminance rescaling.	Image and video editing- texture transfer	TS	Rescaling luminance for artifact removal, texture transfer, seamless cloning, spot removal.
	IQ	[76] 2001	Minimum error boundary cut/ Image quilting algorithm.	Texture synthesis	OS	Texture synthesis, texture transfer.
	IA	[77] 2001	Two phase image analogy involving design and application of filters for image synthesis based on multi-scale autoregression.	Texture synthesis	-	Improved filtering, superresolution, texture transfer, interactive editing.
	ICS	[18] 2016	3D proxies are constructed, structure aware cuboid optimization algorithm, and 3D proxy transformation.	View-aware image compositing	-	Content-aware image compositing and synthesis for creative object design and 3D modelling.
Image cloning	PE	[6] 2003	Guided interpolation and solution of Poisson equation with Dirichlet boundary condition.	Image cloning/editing	TS	Concealment, insertion, feature exchange, inserting objects with hole, inserting transparent objects, texture flattening, seamless tiling.
	SC	[62] 2009	Mean value coordinates (MVC) for seamless cloning of images and videos.	Real-time seamless cloning	TS	Stitching, cloning, matting, selective boundary suppression, healing of still image and video.
		[81] 2009	Variable stencil size diffusion solver for real-time seamless cloning of large image patches.	Seamless cloning	TS	Seamless cloning, animated diffusion curves, reblurring, panorama generation, rendering.
		[82] 2011	New energy term added to Poisson editing which can be realized using efficient sparse linear solvers.	Seamless image composition	TS	Creating new image, appearance preserving, appearance editing.
		[73] 2016	Color basis vectors for maximizing color separation in transition region.	Seamless cloning and compositing	TS	Color control, color adjustment, color correction.
Image creation	IC	[85] 2006	Querying to search annotated image database, graph-cut optimization and user interaction for designing photographs.	Semantic photo synthesis, image creation	OS	Automatic semantic image labelling, automatic object recognition, image synthesis.

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Table 3 (*continued*)

CT	SC	Ref./yr.	Computational approach	Applications	BT	Editing involved
		[50] 2007	Gradient domain solver adapted and subdivided into quadtree for compositing.	Compositing of large images.	TS	Seamless compositing, image region copy and paste.
		[70] 2009	Variational model considering gradient constraint and color fidelity for natural compositing.	Image composition	TS	Color control, mask using random walk, seamless composition.
		[141] 2014	Dominant geometric patch transformation found from sparse distribution for image compositing.	Patch-based image compositing	HB	Image compositing, region blending.
		[19] 2016	Wavelet pyramid, image entropy and feature handling based on the semantic rationality of images are used for image compositing.	Seamless image compositing	TS	Color handling, feature matching, texture matching, seamless composition.
	OI	[52] 2007	Object segmentation with a shape prior and context sensitive blending for inserting new objects on existing images.	Object insertion	TS	Creating novel visual content, transferring shadows, segmenting and blending.
	IH	[66] 2010	Multi-scale appearance transfer for image harmonization before blending the images.	Image compositing	TS	Style transfer, contrast matching, texture and color matching.
	IF	Shen 2014	Boosting function, boosting Laplacian pyramid.	Exposure fusion	TS	Exposure fusion.
Image inpainting /completion	II	[89] 2000	Based on solving partial differential equation (PDE), smooth propagation of information in isophotes direction.	Restoration of old photographs and damaged films	-	Color image restoration, inpainting, magnification and flow visualization.
		[91] 2001	Variational approach based on joint interpolation by solving gradient descent flow.	Filling-in regions of missing data in digital images	TS	Restoration of old photographs, superimposed text removal, and object removal in special effects.
		[88] 2001	Spatial-domain adaptive Weiner filtering algorithm for image alteration task.	Image inpainting	TS	Spot removal, altering or removing shadows, reducing wrinkles.
		[94] 2005	Vector-valued regularization based on variational methods and PDEs, coherent anisotropic smoothing.	image restoration, magnification, inpainting	TS	Color Image Restoration, magnification inpainting, flow visualization.
		[55] 2007	Non-local means and spike detection index (SDI) for defect detection as well as concealment.	Restoration of old color films	-	Defect detection, restoration, correction of damaged region.
		[47] 2010	Variational model combining copy-and-paste, texture synthesis, geometric PDEs.	Image inpainting, resizing, editing	HB	Image inpainting, image resizing, editing and blending images.
		[95] 2014	MRF is used to model Gaussian mixture model (GMM) distributions and texture orientation.	Retouching of facial skin	HB	Detection and removal of wrinkles, texture synthesis.
	ICT	[64] 2007	Gradient based image completion algorithm by solving Poisson equation.	Image completion	TS	Patch filling, removing objects, filling damaged regions.
		[92] 2007	Semantic scene matching and local context matching.	Image completion	TS	Filling missing region.
Image editing	IE	[68] 2006	Connection/covariant derivatives, fibre bundle approach for editing images.	Image editing, inpainting, HDR compression	TS	Scratch fixing, cloning, reconstruction, compression.
		[80] 2010	Replacing Euclidean distance with diffusion distances and Nystrom method for spatial interaction.	Image editing	-	Local edit propagation, edge preserving smoothing and edge aware operation.
	SR	[148] 2002	Lightness recovery algorithm and thresholding the gradient image and reintegrating the results.	Shadow removal	-	Finding and removing shadow.
	IIE	[149] 2001	Invertible contour domain and edge mapping algorithm for high fidelity reconstruction.	Interactive contour domain	-	Deletion, cropping, copy and paste.
		[43] 2004	Graph-cut optimization and gradient domain fusion for editing and creating image.	Interactive image editing	HB	Relighting, stitching panorama, stroboscopic visualization of movement, time lapse mosaics.
		[87] 2009	Image query for image selection, optimization using Graph-cut, and Poisson blending for generation of new images.	Realistic images from user sketches	HB	Creating new images through simple sketching and compositing interface.

Table 3 (*continued*)

CT	SC	Ref./yr.	Computational approach	Applications	BT	Editing involved
		[86] 2009	Candidate image selection and image composition based on user drawn sketch.	Photorealistic Compositing	HB	Compositing photo realistic picture, segmentation.
		[126] 2011	Gradient norm and inpainting by considering the effect of color channels on each other.	Image editing	TS	Object removal, lightness variation, cloning, texture flattening, removing scratch.
	PE	[6] 2003	Guided interpolation and solution of Poisson equation with Dirichlet boundary condition.	Image cloning/editing	TS	Concealment, inserting objects, texture flattening, seamless tiling.
	TA	[150] 2006	Edge-preserving energy minimization for tonal adjustment.	Tone mapping	TS	Tone mapping, color adjustment.
	VE	[45] 2013	Gradient domain blending and optimization of blending boundary based on user provided trimap.	Video blending	HB	Complex object blending (smoke, water, dust), motion difference handling.

CT - Compositing technique, SC - Specific class, Ref./Yr. - Reference/Year, BT - Blending technique, DIM - Digital image matting, BSM - Blue-screen matting, NM - Natural matting, DM - Diffusion matting, PM - Poisson matting, SM - Spectral matting, VM - Video matting, CM - Compositional matting, TTS - Texture transfer and synthesis, IQ - Image quilting, IA - Image analogy, ICS - Image compositing and synthesis, PE - Poisson editing, SC - Seamless cloning, IC - Image creation, OI - Object insertion, IH - Image harmonization, IF - Image fusion, II - Image inpainting, ICT - Image completion technique, IE - Image editing, SR - Shadow removal, IIE - Interactive image editing, TA - Tonal adjustment, VE - Video editing, TS - Transition smoothing, OS - Optimal seam finding, HB - Hybrid blending.

Although techniques have been developed to overcome these issues, the problems are far from being completely solved.

Satellite images, on the other hand, require specialized sensors for acquisition. The weather condition, topographic area, and sensors used can affect the quality of the images captured. Therefore, the satellite datasets also demand pre-processing before registration and blending. Accurate alignment of these images is an emerging area of research in geoscience and remote sensing.

Similarly, *medical* image mosaicing is another field of application with vital challenges. Medical images for clinical examination are acquired using specialized equipments such as endoscope, cystoscope, and ultrasound imaging, which have limited FOV. Using these instruments, it is hard to view the complete structure of the organ in one shot and detect the abnormalities. Recording the corresponding images in video frames and mosaicing all the frames together helps in accessing as well as locating the abnormalities effectively. However, the huge data storage, longer computational time, visible and hidden blood vessels, texture, lighting etc. are the major issues that affect the mosaic generation from medical images.

Image *compositing* has been explored extensively by the researchers. The application domain of compositing is also expanding with the recent demands. Extraction of precise foreground mask and blending it seamlessly over different background is interesting yet difficult problem in compositing. There are still many open issues like automatic image selection and mask generation, less user intervention, complex background conditions, variation in color or texture, illumination difference, shadows, seamless blending, color bleeding etc. which require further research attention.

Mosaicing has vast areas of application in computer vision, and *biometric* is not an exception. Whether it is face recognition or fingerprint detection, image mosaicing plays a key role in generating a complete view from the partial images available. However, in case of face, one reference front image is essential so that the partial images can be mosaiced based on the reference image. Moreover, the facial images sometimes lack distinct features. To overcome these difficulties, novel algorithms need to be developed for biometric applications.

5. Conclusion

Mosaicing is widely used for creating single seamless images by merging a set of multiple images. This paper reviews various state-of-the-art mosaicing algorithms. Salient features of the algorithms with underlying concepts are described. The existing mosaicing techniques have been categorized into different groups based on the attributes such as image type, methodology applied, and specific area of application. A comparison among the existing methods is provided for better selection of a particular mosaicing scheme that works best for a specific task. Future research directions are suggested while discussing the present limitations of the existing algorithms.

Table 4
Registration techniques: Direct versus Feature based.

Properties	Direct methods	Feature based methods
Image information	Whole image information	Distinct features only
Convergence	Limited range	Robust
Invariance	Exhibits photometric difference	Invariant (Geometric + Photometric)
Robustness to outliers	Higher cost and complication involved	Easily achieved using RANSAC
Applicability	Wide range of scenes	Selective scene selection
Computational cost	Cost of every iteration	Cost of all steps involved

Table 5
Blending techniques.

Blending methods	Advantages	Shortcomings
Alpha blending (A)	Reduces sharp transition between images, less computational and memory cost.	Ghosting if window for blending is not optimal, does not work well for complex images.
Feathering (B)	Smoothing of abrupt seams between images.	Loss of high frequency information due to smoothing.
Pyramid blending (C)	Blends both high and low frequency details separately.	Ghosting and double contouring in case of registration misalignment.
Gradient domain blending (D)	Seamless smoothing of color transition between image regions.	Color bleeding i.e. change in color of the inserted object due to boundary interpolation.
Dynamic programming (E)	Avoids ghosting due to moving objects, faster labelling than graph cut.	Energy minimization is along one direction due to which it accounts for the error surface orthogonal to the seam.
Graph-cut (F)	Reduces ghosting due to moving object in the scene.	Comparatively slower, high computational and memory cost.
Watershed (G)	Significantly reduces the search space for optimal cut in the areas of low photometric difference.	Results in over-segmentation of the image which need to be handled using smoothing operation prior to the desired application.
Hybrid (AE), (BE), (CA), (CE), (DE), (DF), (FG), (DA)	Effectively reduces blending artifacts by exploiting the advantages of contributing methods.	Computational burden is more.

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