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Panoramic image stitching using cross correlation and phase correlation methods

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Abstract - Image stitching / mosaicking is the process of aligning multiple images together to form a single high resolution image known as panoramic image. Stitching multiple images of same scene captured from different positions to form a high resolution single image is a challenging task. Images taken by a single snap will permit only a limited view whereas panoramic image allows a wide angle view. In order to create a panoramic image, the simple method is to stitch two or more images of a scene into single composite image. Mainly there are two approaches for image stitching such as “direct approach and feature based approach”. In this paper, we discuss two basic simple approaches of direct method for image stitching. First method is correlation based and second one is phase correlation. The proposed cross correlation method can stitch multiple images having horizontal displacement or vertical displacement with each other. But it cannot handle images having both horizontal and vertical displacement simultaneously. In order to solve this problem, we proposed phase correlation based image stitching that can be used for measuring the motion parameter i.e. both horizontal displacement and vertical displacement present in images. Hence, we can stitch multiple images having both horizontal and vertical displacement simultaneously. In cross correlation based method, three images of same scene with different orientations were put together to form a high resolution panoramic view. But a pair of images were used to stitch together to form a panoramic image using phase correlation based method. The proposed cross correlation method is not completely translation invariant, whereas the phase correlation based stitching is invariant to translation. But the main disadvantages of both methods are that they are not invariant to image scale and rotation.

Keywords- Panoramic image, image stitching, cross – correlation, template matching, phase correlation, registration, blending.

1. INTRODUCTON

A panoramic photo allows a wider view of a scene that is not possible with traditional photography, which includes only a limited view. Image stitching or image mosaicking is a process that combines more than one images of the same scene captured from a different viewpoint to form a high-resolution single image with panoramic views

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[1]. To perform stitching of more than one images into a single panoramic image, we need to identify the exact overlap of these images and then align them into the proper place and order. Image stitching processing can be accomplished in three different steps such as registration, calibration, and blending [2]. Image registration is the primary step in image stitching. "Image registration is the process of matching and aligning two or more images that may be taken at different times, or from different sensors or different viewpoints"[3][4]. Image registration can be accomplished in two ways, either by direct alignment or by feature-based alignments. "Image calibration is used for eliminating the optical defects such as the difference in exposure, lighting, illumination, brightness, and contrast of the input images" [5]. If we are stitching two images of the same scene taken by different cameras at different time and from different viewpoints, parameters such as colour illumination, brightness, contrast, exposure of these images will vary. Hence the stitched image may exhibit these differences. So, to overcome these problems image calibration algorithms will convert all image parameters mentioned above to the same value. The final step of the stitching operations is to blending, that means changing the pixel colours in the overlapped region to avoid the seams. The stitched image may contain artefacts due to various reasons such as exposure differences, change in lighting, object movement and so on. This will lead seams across the stitching process. In order to reduce these artefacts, image blending algorithm can be applied across the stitched image that results seamless panoramic image [6]. This paper proposes a basic image stitching algorithm based on direct image registration. We used cross-correlation and phase correlation technique for image registration. The cross-correlation method is used to find out the patch common to both the images. Image patch is a group of pixels in an image. Here the common patch will be the overlap area of the images. We aim to locate the common patch in both images. To find out the common patch, the similarity between the patches are to be calculated. Cross-correlation is one of the commonly used similarity measurements [7]. The patch-based similarity measurement calculation utilizes the technique of template matching. "A 'template' is a small part of an image" that is to be matched amongst entirely different objects [8]. Template matching operation determines the components of an image which matches the predefined template and locate the position of template in the target image. In our experiment, a patch is considered as the template. For image stitching, we need to iteratively search for the common patch. A patch-wise comparison is done using cross-correlation. This process is continued by changing the patch in both the images and doing cross-correlation. This entire process is repeated until we cover the whole image. The maximum cross-correlation ratio lies in the area at which an exact match is found. Using the location of the common patch we can easily align the input images to form a single image. Necessary brightness adjustments in the source images are to be done for obtaining a good result. In this paper, we are going to propose two separate algorithms for image stitching which utilizes both horizontal and vertical translation with the source image. Cross-correlation based stitching algorithm is not suitable for stitching images in a different scale and orientation. This method cannot stitch images with

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horizontal and vertical translation simultaneously. So, we further propose a phase correlation method for image stitching to overcome the limitations of cross-correlation. The phase-correlation based image stitching algorithms can stitch images with horizontal and vertical shift simultaneously. Hence, phase-correlation based stitching is known as translation invariant algorithm.

The rest of the paper is organized as follows: Section 2 includes a brief description of the general methods in image stitching. Methodology of the proposed method is described in section 3. This section is organised in two subsections. The First subsection introduces the proposed cross-correlation based stitching methodology. The second subsection describes how phase correlation can be utilized for overcoming the limitation of cross-correlation based stitching. The pros and cons of each proposed methods are explained in this section. Section 4 evaluates the experimental results of the proposed methods and followed by the conclusion.

2. GENERAL METHODS FOR IMAGE STITCHING

Based on the registration method used, "image stitching can be classified into two categories such as direct method and feature based method" [9]. In direct method, each pixel intensities of the images are compared with each other to find the most similar pixel. In feature-based technique, all main feature points in input images are compared with all features of other images by using feature descriptors [2].

2.1 Direct (Pixel based) method

The Direct method uses pixel-to-pixel matching for image alignment. It works by comparing all pixel intensities of each input images [1]. The Direct method minimizes the pixel-to-pixel dissimilarity by using certain similarity measurement such as Sum of absolute difference [10], Transformation using Fourier analysis, Cross-correlation, Sum of squared difference [9], Phase correlation [10] etc. In all these methods comparison is done between pixels, so they become complex to operate. The Direct method is also known as area-based technique, region-based technique, pixel-based technique and intensity-based technique. The direct method make use of optimal information for image alignment. This is the main merit of direct method [11]. They calculate the contribution of each pixel in the image. The major drawback of direct image stitching is that they have a limited range of convergence[12] and not invariant to image scale and rotation.

2.2 Feature based Technique

In feature-based technique, features of the images are used for registration rather than using pixel intensity values. There are four main tasks involved in feature-based image registration such as "feature detection, feature matching, image alignment, and image blending"[12]. In feature detection, distinctive features such as lines, edges, curves, corners and any other salient features are extracted by using any of the feature detectors. In the feature matching stage, these extracted features of both the input images are compared with each other. The matching features can be used for estimating global correspondence and geometric transformations between images [10]. The main characteristic of feature detectors is that they

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invariant to image scale, rotation, translation and image noise. There are different types of feature detectors such as, Harris corner detector[13], Scale Invariant Feature Transform (SIFT)[14], Principal Component Analysis SIFT (PCA-SIFT)[15], Speed Up Robust Feature Transform (SURF)[16], Feature from Accelerated Segment Test (FAST)[17], Oriented FAST and Rotated BRIEF (ORB)[18]. Proper alignment can be done using the estimated transformation. Finally blending algorithms are used for colour correction and quality enhancement of the stitched image. The ultimate aim of blending is to improve the quality of the output image.

3. PROPOSED METHODS

The proposed methods for image stitching are based on cross-correlation and phase correlation technique. Both of these methods are pixel-based technique. The Similarity between input images is measured using pixel intensity values. Cross correlation-based image stitching method is implemented by stitching three consecutive images of the same scene that have horizontal or vertical displacement. Phase correlation-based stitching is used for stitching pair of images having both horizontal and vertical displacement simultaneously. Using these two techniques, any number of panoramic images can be constructed from any consecutive images which have translational displacement.

3.1 Cross-Correlation based stitching

Cross-correlation is the basic approach for image registration. It is mainly used for template matching or pattern recognition. It gives the measure of the degree of similarity between an image and a template. For a template T and image, I[19], which can be called as a target image, i.e. T is small compared to I. The cross-correlation function measures the similarity for each translation.

$$C(u, v) = \sum_x \sum_y T(x, y)\, I(x-u, v-v) \quad (1)$$

Where,

C (u, v) is the correlation ratio between template image and target image.

T(x, y) is the template image

I(x, y) is the target image

(u, v) is the displacement parameter

If the template matches the image exactly, except for an intensity scale factor, at a translation of (u, v), the cross-correlation will have its peak at C (u, v) [19]. By computing cross-correlation over all possible translations, it is possible to identify the degree of similarity for any patch known as a template-sized window in the image. A template image or patch image will be a sub-image of the source image, which is always smaller than the source image. In template matching, we need to identify where the template image is located in the source image. To find the exact location of the template image in the source image, the template image is moved across the source image and cross-correlation is performed between the compared template image and source image portion. The highest cross-correlation lies in the area at which the template is located in the source image. We used this idea for creating a panoramic image of a scene under image stitching.

We created a data set which comprises of five different sets of images such as a book, keyboard, human face, building, and outdoor view. In each set, a group of three images having horizontal

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displacement or vertical displacement are used for the experiment. All these three images were captured in two different ways. The images are captured by shifting the camera only in the x-direction to obtain horizontal displacement. Similar way the images are captured by shifting the camera in the y-direction to obtain vertical displacement too. Thus, three source images are used for the creation of a panoramic view of the image by applying image stitching algorithms. This method can be extended to any number of images depending upon the computation facility available by changing slight variation in the algorithm.

The flow chart of the proposed method is illustrated in Fig. (b). In general,"image stitching consist of mainly three operations, calibration, registration and blending" [1]. Image calibration aims to remove the optical defects such as distortion, the difference in illumination, contrast and exposure between input images. Images are properly aligned into a single image after identifying the overlap between them. This operation is generally known as image registration. The stitched image's quality is enhanced by blending the seam across the stitch. The flow chart as shown in Fig. (b), explains how three images of a scene can be stitched together to form a single panoramic image [19]. Initially, the first two images are stitched together to form a single image. Later, this output image is stitched with the third image. Before registering these images, all three images are normalized to the same exposure and contrast. Normalization is done by mapping intensity values in the images to a new value. The new value can range from zero to one. The values below zero are converted to zero and value above one are mapped to 1. Using this operation all image intensity values are converted to the same value. The first two images are aligned by finding the common patch between them. For finding common patch initially, we selected a sub-portion of both images with equal size as patch. The patch can be selected by specifying the boundary coordinate value of the required patch. The size and shape of the patch can be defined based on the translation involved in the input images. i.e., whether horizontal translation or vertical translation. The cross-correlation is performed iteratively between all patches in the images. Initially selected patches are compared by performing cross-correlation operation between them as specified in equation 2. In the next step, another patch in both images are selected and cross-correlation is performed in the same way. This process is repeated until all patches cover the whole image. Among the correlation coefficient C, the value returned by the two-dimensional correlation operation, the maximum correlation coefficient is selected. The location of this maximum correlation coefficient will be the location of the common patch of the image. In the next step, we calculate the distance/ displacement/ offset between the common patches of the images. Images are aligned together to form a single image by applying translation based on the calculated displacement parameter. Next, we have to stitch the third image with the stitched image formed from the first two images. For this, we select a patch in both images. Cross-correlation is performed as specified in equation 2. Different patches are selected in both images. Among maximum correlation value, location of overlap is identified. Hence translation alignment is performed between third images with a stitched image from the first

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two images. The entire operation is depicted in fig. b) is explained in detail in the next session.

3.1.1 Template Matching

"Template matching is the process of finding the portion of a source image I, which matches with a template image T"[20]. Generally, template image will be smaller than the source image. To find the position of the template T in the image I, a pixel-wise comparison of the image I with T can be performed. Cross-correlation is the simplest method to perform this comparison [21][7]. General working of a template matching is depicted in fig a.

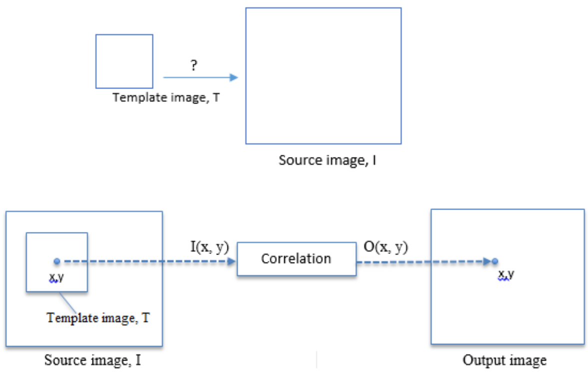

Fig. a) Template matching

We have two images namely template, T and source image, I. We need to calculate the corresponding points between them. The correspondent point can be identified by utilizing any of the similarity measurement technique. Similarity can be measured by performing cross-correlation operation between T and I. To find the location of T in I, T is shifted across the source image and at each shift, cross-correlation is performed between them as given in equation 2. Initially, the similarity between template image, T and top left portion of the source image with the same size is calculated by performing cross-correlation operation between them. In the next iteration, the template image is shifted to the next portion of the source image and the cross-correlation is performed in the same way as above. This process is repeated until it covers the entire portion of the source image and hence the computed numerical value that indicates the similarity between the template image with the source image [21].Finally, among the cross-correlation value calculated in each iteration, the highest cross-correlation value is selected. The location at which the highest correlation value found, will be the location of the template image, T in the source image, I.

In our experiment, we used the idea of template matching for identifying the common patch in source images. Here each patch is considered as a template. In image stitching operation, all set of input images contain a common area i.e., the overlap region. Identifying the overlap area of the images is the most challenging task involved in image stitching. This overlap can be identified by performing the cross-correlation operation between image patches. Different patches in source images are created and compared with each other. The working of cross-correlation is explained in the next session. The common area will have a maximum correlation coefficient [7].

3.1.2 Colour Adjustments

One of the limitations of cross-correlation image stitching that, it is unable to identify the exact match between patches having entirely

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different brightness. If anyone of the source images contains a huge variation in brightness or exposure in the common area, cross-correlation will not result in maximum correlation ratio at that portion i.e. similarity will be low even they are common portion in both images. In other words, if the common area of the input image has different brightness or colour illumination due to the variation of camera settings and lighting conditions present at the time of acquisition. Simply performing cross-correlation directly on these images will not result a proper match. So, in order to find the exact common patch between all input images, the brightness and colour illumination should be normalized. Another way to solve this problem is by using normalized cross-correlation[7]. It is done at every step of equation 2 by subtracting the mean and dividing by the standard deviation. That is the cross-correlation of a template, T(x, y) with a target image I(x, y) [7]. It can be done by using equation 3.

In the proposed algorithm, before cross-correlating the input images, the brightness and contrast values of all images are normalized into the same value. Individual image adjustment has to be done by mapping the intensity values to the range between zero and one. Any values below zero are converted to zero and any values above one are converted to one. Hence extreme variation in the contrast can be eliminated. This is repeated for each image. Hence brightness can be adjusted according to each image. In our experiment, we have three input images; images of a building captured in horizontal displacement as given in Fig. c, Fig. d, and Fig. e. Intensity values of all images are adjusted to a value ranging from zero to one. So, the correlation operation can find an exact match. Contrast and exposure adjustment alone is not enough for making the input images with the same colour of illumination and brightness values. This only improves the accuracy of the correlation. A Further operation for enhancing the quality of the stitched image can be done further by image blending algorithms, if necessary.

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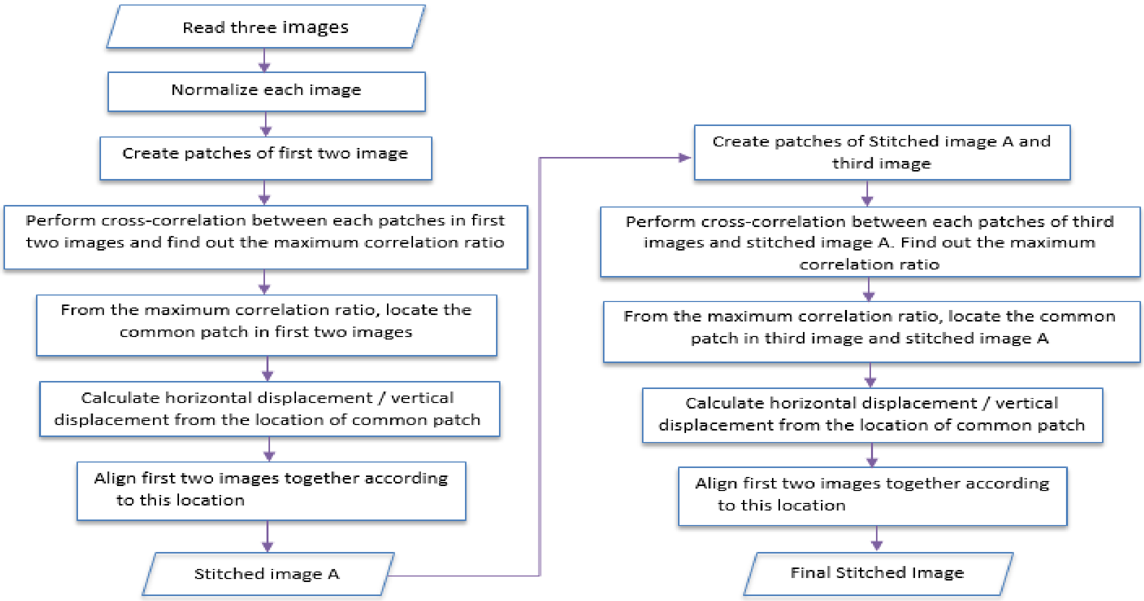

Fig. b) Flow chart of cross-correlation based image stitching

3.1.3 Cross-Correlation

Many similarity measures are available for matching images [10]. Cross-correlation can be used as a similarity measure. They assume a linear relationship between the image intensities [23]. The aim is to maximize the product (cross-correlation) of the two aligned images. In the proposed method three input images of the same size are used. Two separate algorithms are proposed for stitching images that have horizontal and vertical displacement. Consider the first two images I1 and I2 of size M x N. Where M is the total number of rows and N is the total number of columns. In the case of the horizontal displaced image, two patches with size M x 5 are created in both images. Cross-correlation is performed between these patches. Iteratively different patches of the mage are created and cross-correlated with each other until it covers the whole area of both images. The cross-correlation operation given in equation 2, will return the cross-correlation ratio between the compared patch. Among the cross-correlation coefficient calculated in each iteration, the maximum one is selected. The patch that is common to both images will have a maximum correlation value. The location of this common patch is saved for the alignment of the input images into a single image.

For a template/patch T and image I which is called as target/source image, where T is small compared to I. The two-dimensional cross-correlation function measures the similarity for

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each translation of T over I [19]. It can be calculated as given in equation 2.

$$C(u, v) = \sum_x \sum_y T(x, y)\, I(x-u, v-v) \quad (2)$$

Where,

C (u, v) is the correlation ratio between template image and target/ source image.

T(x, y) is the template image

I(x, y) is the target image

(u, v) is the displacement parameter

In the proposed method different patches of the first image is compared with every patch created with the same size of the second image. The patch size is Mx5. The comparison is done by cross-correlation as given in equation 2. Position of the overlap in input images varies according to the translation we applied while acquiring the image. So, different patches must be selected in both images and compared with each other to identify which is the overlap portion. In a general template matching problem, the template image is already defined. Our aim in such case is to find the position of a template image in the target image, whereas in image stitching initially, we do not know which is the overlap portion/ common patch in the images. So, different patches are to be selected and compared with each other. The similarity is measured by performing a cross-correlation between the patches. In each iteration, the measured similarity i.e. the correlation coefficient C, is saved. Finally, we need to calculate the maximum correlation coefficient among the correlation values measured in each iteration. This maximum correlation coefficient lies in the area that is common to both images that will be the common patch/overlap. Using the coordinate value of the common patch, we can calculate the displacement parameter/ translation parameter/ offset of the common patch of input images. Input images can be aligned to produce a composite panoramic image. Blending can also be applied across the patch, if necessary. As mentioned above, we used three images for stitching as given in Fig. c, Fig. d, Fig. e. Initially Fig. c and Fig. d are stitched together to form Stitched image A. The cross-correlation and alignment process is repeated with the third image given in Fig. e and stitched result of first two images called stitched image A, as shown in fig. b. Patches of the same size are selected in both third image and the stitched image A. Cross-correlation operation is repeated as done in the case of first two images. The maximum correlation value is selected. From the location of the common patch, its displacement parameter/ translation parameter is measured. This displacement parameter is used for aligning the third image with the stitched image A. Finally, we obtain the expected stitched image as output as given in Fig. f.

One of the limitations of cross-correlation is of brightness variation exists in the common patch, the correlation coefficient will not be maximum for that patch. i.e., an exact match cannot find. To overcome this limitation normalized cross-correlation can be used [10]. This is done at every step by subtracting the mean and dividing by the standard deviation. That is, the cross-correlation of a template, T(x, y) with a target image I(x, y) [7]. It can be done by using equation 3.

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$$1/n = \frac{\sum_{x,y} (I(x, y)-I_{av})\ (T(x, y)-T_{av})}{\sigma_I\ \sigma_T} \qquad (3)$$

Where,

T(x, y) is the template image/ patch

I(x, y) is the source/ target

n is the number of pixels in T(x, y) and I(x, y),

I_{av} is the average of I

σ_I is standard deviation of I

σ_T is the standard deviation of T [7].

Another way to overcome the limitation of handling images with exposure difference is that we can adjust the brightness and colour illumination to a uniform value. This approach is used in the proposed method for stitching. The ultimate results of both approaches will be the same.

3.1.4 Image Alignment and Blending

Image alignment and blending are the final steps of image stitching. We aim to stitch three images of the same scene into a single composite image. The input images are acquired from different locations. A linear relationship exists between the input images, i.e., images are acquired by shifting the camera in either in the horizontal direction or vertical direction. Only translation operation is involved in the acquisition of images. So, the necessary transformation needed to align these three images are two-dimensional translation operation. But the problem is that we need to eliminate the overlap between the images before aligning them. This problem is solved with the help of cross-correlation as mentioned in the above. Common patch/ overlap identification is already done with two-dimensional cross-correlation operation. Using the coordinate value of the common patch, the displacement/ offset/ translation parameter can be calculated. The two-dimensional translation is applied using this displacement parameter. The translation operation varies according to the type of translation involved in the input images. i.e., whether the images are horizontally displaced or vertically displaced. Image alignment for these two different types is explained in the following subsection. Blending can be applied across the stitching for enhancing the quality of the final image. When the input images are taken from different places, the adjacent pixel intensities across the stitching may differ due to the change in lighting conditions. This will result in a visible seam across the stitch [5]. Image blending algorithms are applied to remove this visible seam. There are two methods for performing image blending. One is called “alpha blending” and the other is called “Gaussian pyramid”[24][25]. Blending is not necessary if the input images are properly aligned and no difference in exposure exists between the input images. In the

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proposed image stitching algorithm, blending operations are not used because variation in exposure was very low and necessary brightness adjustments and exposure adjustments are already done on the input images itself as mentioned in colour adjustment section.

3.1.4.1 Horizontal displaced image

Horizontal displacement is calculated from the location of the matched patch. First, we place the second image completely (including the overlap region) into the output frame, then the first image is placed, starting from the left boundary of the overlap. Fig c), Fig. d) and Fig. e) shows three input images of the building that are captured by horizontally shifting the camera from left to right direction, with a constant vertical position. Fig. f) shows the stitched image. Fig g), Fig. h) and Fig. i) shows three input images of a keyboard and Fig. f) shows the stitched image.


Fig. c) Input Image 1


Fig. d) Input Image 2


Fig. e) Input Image 3


Fig. f) Stitched Image


Fig. g) input image 1


Fig. h) input image 2


Fig. i) input image 3


Fig. j) Stitched image

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3.1.4.2Vertical displaced image

In the same way, as in the horizontally displaced image, vertical displacement is also calculated from the location of the matched patch. We placed the second image completely (including overlap region) into the output frame, then first image, starting from the top boundary of the overlap. Fig. k), and Fig. l) shows two input images that are captured by vertically (y-axis) shifting the cameral with a constant horizontal (x) position. Fig. m) shows the stitched image.

Fig. k) input image 1 Fig. l)input image 2 Fig. m) stitched image

The blending methods explained above is in the case of stitching of two images. In our experiment, we stitched three images together. In this case, we used the resultant image of the first step as the target image in the second step and repeat the same procedure for stitching the third one. The same algorithm can be extended to stitch any number of images.

There exist some drawbacks for cross correlation-based image stitching method viz. if two same patches exist in the source image to which template is matching, then there may be a chance for wrong matching instead of the exact match that is known as an ambiguous match. Hence, the stitched image will not be a correct combination of the input images. Another problem of the cross-correlation technique is that, if the brightness or illumination of input image varies, the resultant image exhibits the difference and the matching cannot guarantee to perform correctly. The proposed correlation algorithm can be applied only in the case where input images contain horizontal displacement or vertical displacement, i.e. images varies only by translation. Therefore, the correlation-based image stitching algorithm is translation invariant and that all the input images have the same size.

3.2 Phase correlation based stitching

The cross correlation-based stitching algorithm explained in section 3.1 can handle either horizontal displacement or vertical displacement. Two separate algorithms were used to calculate both x-axis shift and y-axis shift. This limitation can be overcome by using phase correlation-based stitching, which can handle images with both horizontal and vertical displacement simultaneously. The phase correlation technique can be used for finding the displacement value between two inputimages [26].

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3.2.1 Methodology

Here we used two sets of images containing images of book and images of outdoor view. In each set, two images were used as the input image for stitching. The method is explained below by using the second set of images as given in Fig. j and Fig. k.

Consider two images $I_1(x)$ and $I_2(x)$. $I_2(x)$ is a translated version of $I_1(x)$. i.e., $I_2(x)$ is captured by both horizontal shift and vertical shift. The horizontal displacement between input image $I_1(x)$ and $I_2(x)$ is denoted by Δx_1 and the vertical displacement is denoted by Δx_2. The Δx_1 and Δx_2 are called motion parameter or displacement parameter. The relation between $I_1(x)$ and $I_2(x)$ can be written as given in equation (4).

$$I_2(x) = I_1(x+\Delta x) \tag{4}$$

Where,

$$x = [x1\ x2\ ]\ ,\ \Delta x = [\Delta x1\ \Delta x2\ ] \tag{5}$$

Their relationship between these two images can be expressed in Fourier domain as given in equation (6)

$$F_2(u) = \iint I2(x) e^{-2\square j\omega Tx} dx$$

$$= \iint I1(x+\Delta x) e^{-2\square j\omega Tx} dx$$

$$= e^{2\square j\omega Tx} \Delta x \iint I1(x^{`}) e^{-2\square j\omega Tx^{`}} dx \tag{6}$$

Where $F_2(u)$ is Fourier transform of $I_2(x)$ and $x^{|} = x+\Delta x$ denotes the coordinate transformation. By performing phase correlation between Fourier transform of two images Δx can be computed as given in equation (7) [26].

$$C = F_1 \circ F_2^{*} \tag{7}$$

Where F_1 is the Fourier transform of $I_1(x)$, F_2 is the Fourier transform of $I_2(x)$, ^{o} is the element-wise product, and * denotes the complex conjugate [26]. The peak's location of this function given in equation (7) points to the motion parameter (Δx_1 and Δx_2) [26]. Fig n) shows input image 1, Fig. o) shows input image 2 taken by both horizontal shift and vertical shift with respect to Fig. n), and Fig. p) shows the stitched image as a result of the proposed algorithm.

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Fig. n) Input image 1

Fig. o) input image 2

Fig. p) Stitched image

The main limitation of phase correlation-based image stitching is that the output image after stitching may contain empty areas as shown in Fig. p). So, some image in-painting algorithm is needed to fill such areas. Phase correlation-based image stitching is not invariant to image scaling and rotation. Another drawback of phase correlation-based image stitching is that, if some object movement is happened in between the acquisition time of input images, a basic translational alignment is not enough for proper blending of the source images, because the object movement results in misalignments in the output view. The motion between two image frames is called optical flow [26]. The proposed Phase correlation-based stitching algorithm is not capable of calculating the optical flow.

4. RESULTS AND DISCUSSION

The algorithms discussed above were implemented in MATLAB. Five sets of images viz. book, keyboard, human face, building, and outdoor view were used for cross correlation-based stitching and two sets of images of a book, outdoor views were used for phase correlation-based stitching. Using cross-correlation method, in a single experiment, three images which are horizontally displaced with each other's stitched together to form a single image. This method is repeated for all other sets of images too. The cross correlation-based method is also used for stitching vertically displaced image pairs. Total of five different groups was stitched likewise. Necessary brightness and contrast adjustment have been done as a pre-processing for all input images to make the correlation operation more efficient. To identify the common patch in the images, two-dimensional cross-correlation is applied across each patch. From the coordinate positions of the common patch, displacement parameter is calculated and then aligned images properly by applying two-dimensional translation operation. Using phase correlation-based image stitching algorithm, pair of images those horizontally and vertically displaced to each other are stitched together to form a single panoramic image. By using phase correlation method motion parameter between the overlap of input images, i.e., the horizontal displacement and vertical displacement between input images are calculated. The overlap between the input images is identified by applying a Fourier transform based method. The element-wise product is calculated in the Fourier transform of the first image and complex conjugate [4] of the second image are

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calculated as given in equation 7. The overlap region will have a maximum element-wise product. It has been found that the correlation-based template matching algorithm[7] works well in the case for stitching images that are varied by translation only. Both cross correlation-based method and phase correlation-based stitching algorithm has its pros and cons. Depending on the application and pictures used for stitching any of the above methods can be used for image stitching. If we need to stitch images that are either horizontally displaced with each other or vertically displaced, cross correlation-based stitching can be applied to get a panoramic image. If we need to stitch two or more image having both horizontal displacement and vertical displacement phase correlation-based stitching is suitable.

5. CONCLUSION

The proposed cross correlation-based algorithm is a sub-pixel image stitching algorithm, i.e. instead of comparing each pixel separately, a group of pixels (patch/sub-pixel/template) in the input images were extracted and compared with each other. This is the basic level of image stitching that can be applied for adjacent disordered images (both horizontally and vertically). Image are aligned together by calculating the offset between the matched patch and then placing them into the output frame by translation. Phase correlation algorithm is well suited for stitching images with both horizontal and vertical displacement. We conclude this paper by stating that the correlation-based image stitching and phase correlation-based image stitching are translation invariant but not scale and rotation invariant. As a future work more sophisticated algorithm can be used to overcome the limitation occurred in these two approaches.

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