Performance Enhancement of Image Stitching Process Under Bound Energy aided feature matching and Varying Illumination Environments

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***Abstract*:**
Stitched images is a method that mixes several images or images of the intersecting perspective field to create a high-resolution panoramic image. In the field of medical imagery, satellite data, computer vision, military automatic target identifiers, we can see the importance of image mosaicing. The fields of computer vision, photography and computer graphics are currently being researched on image stitching and video stitching. Registration of images includes five major steps: detection of image features and its description; matching features; outsider rejection; deriving transformation function; and reproduction of images. Stitching images of similar images is a difficult job when images are captured in variable light conditions. In this paper, we have examined image panorama development which is based on seamless image stitching to overcome the above mentioned problems by adopting the de-hazing technique on the acquired wide view scenes. This is achieved further before identifying the image functionalities and bound energy-energized features that match the image's invariant scale attributes (SIFT). Compared to the current image stitching techniques the experimentation of the suggested model uses squared distance to match the features. The suggested seamless stitchable technique is assessed on the basis of metrics VSGV and HSGV called as "Vertical Square Gradient Value" and "Horizontal Square Gradient Value" and respectively. Analysis of the aforementioned stitching algorithm aims at reducing the amount of computation time and inconsistencies in the stitched result obtained.

Keywords: *Bound Energy, ASIFT, FAST, FREAK, Panorama.*

I. INTRODUCTION

The image mosaic is a multi-correlation image stitching that creates a bigger picture broad-scale picture [4,16]. Image mosaicing is an unpreventable implementation method, such as creating panorama images, extraction of objects, video compression, object insertion video stabilization and object removal. The method can be defined as follows: suppose two pictures (I1) and (I2) are present with some common components (W). we want to combine these two images into one image with overlapping the common parts. This is what we call the image mosaicing [20] precisely. The first stage in Image Mosaicing is the extraction of key image features in which both images are identified. Image registration relates to a collection of images geometrically aligned. Two or more digital images from a single scene taken from various sensors can consist of the different sets of data from different periods or from different points of view. Next stage is image registration, where two or more pictures are aligned from one stage or the same thing from another stage. Next is stitching after image registration. When stitching or image fusion every image is transformed into a single large canvas according to its registration parameters, and the final step is to create an image fusion, so that the transfer from an image to another can be smoother. Thus, the fundamental measures in imaging technique are shown in this diagram.

Many picture stitching tools, including Lowe's method [13] have been created [11], etc. But these techniques are having issues as they generate unsatisfactory outcomes, viz. non-alignment of overlapping parts and a bad performance of stitching [14].

The other techniques included Optimal seam choice [19], panoramic weaving [22], time-consuming method [5], and having the critical bottleneck [18] [21].

Bound energy-supported function matching is the major contribution to this paper: this paper includes feature matching depending on the bound energy system. Due to the efficient depiction of non-linear information and suppression of outlier features, the key features of the images are determined by the use of bound energy. The noise-tolerant behaviour of bounding energies seeks to address external effects in seamless mosaicing process [8,10]. The remaining paper is structured accordingly as follows: Section 2 examines the associated techniques in the stitching of images and describes the issues related with the recent techniques. The proposed mosaicing technique with the description and mathematical formulations is described in Section 3. The findings acquired are discussed in Section 4 followed by the conclusion in Section 5.

II. LITERATURE REVIEW

In 2011, the suggested algorithm of Affine-SIFT (ASIFT), which is extension of SIFT technique to include a affine invariant tool, was adopted by Morel and Guoshen [23]. It tried to demonstrate by a proposed method that a completely affine invariant image matching is feasible for mathematical arguments. The detector family FAST was presented by Rosten et al. [12] (2010) in 2010. Furthermore, the basic and repeatable section study has been transformed to the FAST-9 key feature detector that which has non-matching machine learning in terms of processing speed. The resulting detector has great repeatability despite the velocity related design. The new image key feature descriptor, which was influenced by system based on human vision and the retina, called “FREAK-Fast Retina Key Point” was presented in 2012 at Alahi et al. [1] (2012). By matching image intensities effectively over a retinal sampling model a cascade of binary strings is calculated. The methodology used is correlation to stitching processes, as pointed out by writer Lei et al (2016) [6], but its drawback lies in messy noise. Writer Ma.et. al (2015) [18] The Hamming distance is used for estimation of similarity but the Illumination variation is vulnerable. Writer and Huang. Al (2015) [5] utilizes the concept of greatest chance to match, but sensitively applies to initial results and low- dimensional data. The RANSAC and Weighted Average Bending Algorithms (WBAs) were used by Ma et al. (2016) [18] to find optimal affine transformations and smooth out intersecting areas intensities, respectively. However, the similarity metric taken here on the basis of hamming distance examines slight variations from its initial intensity and consequently declines to find out the exact image feature similarity between the images under different lighting conditions [17]. Stitching similarities with the highest probability assessment method was determined by Huang et al-2015[5]. The probability estimation method is susceptible to initialization and the amount of samples despite its ability to manage differential image intensities. In Song et al. (2015) [14] the concept of chaos theory was introduced to determine the similarity of images. Chaos theory is a famous smart technique, while computing efficiency is increased by the difficulty of image representation. Thus this thorough analysis of the results of the similarity analysis, methodologies and their evaluation in the terms of the methodology adopted indicates that the existing piece of literature indicates that less data is available regarding account of environmental limitations like illuminations variation and noise variation, particularly in the image stitching involving low light images.

III. IMAGE MOSAICING BASED ON BOUND ENERGY AND SIFT METHOD FEATURE MATCHING

In this section a thorough description about the proposed presented methodology has been convened. Initially, images with overlapping fields are adopted as inputs for stitching processes. The basic sequence of the proposed technique is explained as below:

Because the noise is unavoidable in general and especially when the sensor noise when the image illumination is low, the noise removal is carried out before processing. The suggested image stitching technique, in comparison with standard image stitching techniques, helps to remove noise to increase the computational complexity of the suggested method. The key features of the images are essential for precise image mosaicing process. Feature description or extraction is undertaken here by SIFT method as the SIFT process is considered to be invariant in the image for scene rotation, movement, blurring, etc. The features gathered from the images are matched by process of feature matching. The overlapped images have a cost function based on the estimated maximum value of bound energy. The features are adjusted to the cost function. The matching image shows the matching of the function.

The aim of the image match is to identify images on the basis of their maximum correlation or matching with their corresponding points. The inliers among compatible homograph images are chosen using RANSAC. In the image matching, the bundle adjuster adjusts errors caused by the transposition of pair-wise homographs. The squared image distance, i.e. total of two image stitched squared distances, is minimized in comparison to the image parameter for bundle adjustment. Finally, images are blended. The blending of images leads to an overlapped image mosaic that is recognized as the input.

A. SIFT feature extraction:

The fundamental steps involved for feature extraction in SIFT algorithm are: (a) Scale Space Extrema detection (b) image key feature points location (c) orientation assignment and (d) key- point extractor [9]. The key points descriptor is the key step in the process for the extraction of the SIFT function (Brown and Lowe, 2007). The key point locations for the SIFT features are described as the maximum and minimal outcome of the distinction between Gaussian and input images related to the scale. The stages also adapted to guarantee that the key feature points for the corresponding feature are more stable.

Scale-Space Extrema Detection: The key features are nothing more than the point of interest. The images are successfully converted with Gaussian filters in distinct scales by using the Gaussian Differential

Function (DOG). The DOG feature enhances the corners of the pictures.

Precise localization of key points: extrema scale-space monitoring produces more key points. On the basis of its stabilization (David and Lowe, 2004), the key points are chosen in the key point localization [9].

Orientation to key feature points: the local orientation of the image gradient is allocated to the key points in this step. Therefore, SIFT key features as mentioned by David and Lowe, 2004 [9] can achieve an invariance of image rotation.

key point extractor/descriptor vector: In the case of descriptor key feature point step [2], the histograms are computed from the direction and magnitude of the key point features. The neighbourhood scores of the key points are represented in each histogram. By placing a weighted Gaussian function concept in the gradient magnitude with the scale corresponding to the Descriptor Window length, histogram results are transformed into a descriptive vector.

B. FREAK descriptor

The first section is a model of sampling that indicates where to sample points from the region neighbouring the descriptor from the above texts. The first part is a sample method. Second, orientation compensation that provides a mechanism for measuring the orientation of the key point and rotating it in order to account for alterations in rotation. And finally sample pairs that explain which pairs are to match in the ultimate descriptor building.

C. Features from Accelerated Segment test features (FAST)

FAST is basically a corner detection technique that is applicable in many computer vision usages to obtain key feature points and use them subsequently to track and map objects. The Edward Rosten and Tom Drummond FAST corner detector was originally created and published in 2010[12]. Its computation effectiveness is the most important feature of the FAST corner detector. In addition, better efficiency in terms of time and resources can be achieved when machine learning methods are employed. Because of its high-speed output the FAST corner detector is ideal for real-time video applications.

D. Affine-SIFT (ASIFT) [23]

The major component of the SIFT technique is the concept of combining simulation and normalization. The SIFT detector standardizes rotations and transitions, simulating all Zooms in the search image and database. It is the only fully scale-invariant technique because of these characteristics. With sufficient accuracy ASIFT simulates all distortions due to changes in the orientation of the optical axis of the camera. The SIFT technique then operates. In other words, ASIFT simulates three parameters: the longitude angle, the scale, and the latitude direction (which is equivalent to the rotation) and normalizes the other three. The main observation is that while a tilt distortion is irreversible because of its failure to commute the blur, the bend can be balanced by visually simulation of an identical angle in the horizontal path up to a shift in scale. Unlike standardization techniques, ASIFT simulates the whole associated invariance, which results in this non-commutation method. Contrary to the previously asserted simulation of the full affine space with the required affinity space sampling is not prohibitive at all. The ASIFT complexity is further reduced by a two-resolution scheme to about twice that of SIFT.

E. Bound energy based feature

There are various Commonly used methods for obtaining and matching appropriate image key features or likelihood information [6,5,10]. However, the match must be made between two images which overlap in parts, and numerous images must be overlapped one after the other. The same must be followed. Especially while matching features between areas overlapping with more than one image requires either maximizing correlations for greatest matches through resemblance or reducing different incorrect matches concurrently by minimizing entropy. It is interesting that both are mutually beneficial. Our motivational considerations are to decrease different matches, which do not belong to overlapping areas, while maximizing the similarity of the overlapping regions, which have spatial and photometric variations in overlapping image regions.

We recall and use the bound energy formulated by Watanabe in attempt to merge the above two features (Ganesa Moorthy and Nandhini Devi, 2014) [3] as a bound energy allowed feature matching. The bound energy used to match the image involves determining the additional energy of the image-related features and selecting the vector element, with the maximum features of the images having highest bound energy levels. Post-extracted features are used to stitch images. Bound energy is the summing up of entropy as well as of the total correlation [13]. Below are the steps involved in the bound energy matching features. The maximum H feature is essentially chosen as an appropriate key image feature among the initial image feature vectors, bound energy is which can be called in other words as a transformation of the image vector. It offers accurate functionality vector statistics. In this case instead of discovering the similar image key feature vectors, the suggested method discovers the resemblance among the related successive key feature vectors of overlapped parts of image pairs, also are known as the optimal vector for bound energy. This gives the image points a more accurate similarity.

In addition, entropy is usually used to identify comparable key features described by authors Shu and Wang-2013[13]. If the bound energy value of the key feature vector is calculated for similar overlapped parts of image pairs, it signifies that key feature to be unmatched if the bound energy value decreases when an image feature is neglected. The entropy distribution helps in predicting the correct value in information theory, even if the significance of the attribute is not known.

Eij= -Pij log Pij ------ 1

where the result of in (1) is considered a proportion depending on the connection and the total correlation, both of them owing to the different characteristics are provided as (2).

Pij = |Cij|/ TCr ------ 2

Now, the correlation between the standard feature vectors of images I1 and I2 is recognized as

Cij= 1-(1/2N) di^2 ----- 3

Independent objectives are the optimization of total correlation and joint bound energy in which case total correlation value supposed to be maximized and joint bound energy has to be kept to a minimum. Bound energy is of similar relevance to all features. The actual array of information however is weighted differently. Reverse sigmoid [13] (Shu & Wang, 2013) is used to measure the entropy on each feature.

H= Wij + Hij ------ 4

Where the value of Hij is the combined entropy component

Hij= Eij + Cij ------ 5

Note Hij also indicates the bound value of energy without

Wij= 2/ (1+e-Hij) ----- 6

F. Image matching and blending

Images with maximum matching key features are collected in the image matching. Finally, these images collected are stitched on a panorama image development. Because in this case each image which is acquired to overlap the other, the key features can match each image. Thus a small number of images which are having overlapping are necessary to match the image so that a good solution can be chosen for image geometry. The objective of RANSAC (Li et al., 2008) [7] is to select an image of homographic function matches between images. The key image feature point with a right relationship with the input image is related to inliers and the key feature point is called outlier with non-related adequate matching parts of overlapped image pairs. By rejecting outliers achieved through model set parameters (Yang and Guo, 2008) [15], RANSAC is useful for acquiring a significant data set points related to the inliers. The model parameter set is the correct or compatible homography with the higher support. RANSAC's inliers points are verified by probabilistic models. The probabilities model described by Li et al-2008 [7] basically makes comparison of the probability of a match between outliers or inliers. Using RANSAC, image matches are achieved between both images. The issue is to suppress the acquired image error. The error has been minimized by the use of the cluster adjusters [2] (Brown and Lowe, 2007). The parameters related to the homography matrix are continually being optimized in the bundle adjustment. This optimization is done until the remaining error caused to the build-up of the image is minimized.

Blending of images which is based on matched images is the fusion / integration of images. The RANSAC image matching results in the geometry of image stitching, with the visible seam in the overlapping area as described by Li et al-2008 [7]. The basic aim of an image blending is to seamlessly mosaicking process done for images to generate panoramic images. Some techniques, in addition to fusion, have to be used to adequately reconstruct images having blur, overlaps etc, in panoramic images. These are basically: 1) Straightening 2) Mixing multi-band explained by Brown and Lowe, 2007,3. Gain Compensation. Straightening means that the wavy affect is efficiently removed from the output panoramas. Compensation is the method adapted to overlap the brightness error in the image fusion. The edges of images visible even when compensation is provided are reduced by method of multi-band mixing, parallax effect, error in registration, and so on.

IV. EXPERIMENTATION AND RESULTS

A. Experimentation Procedure

The studies are done in an Intel Core i3 Processor computing hardware having 2 GB RAM with Windows operating system in the computer. The MATLAB R2014a is the basis for simulation. This is the testing method. At the beginning, the input for the image stitching system is provided to two images having overlapping region without lighting or noise impact. The proposed system provides a panoramic image of quality with less computation time. An image is given as the input with the noisy environment. Five images for stitching are used in experiments with noise variations. Invariance of the noise effect is the generated panoramic image. Two efficiency metrics namely "Horizontal Square Gradient Values" and "Vertical Square Gradient Values" as described by author Song et al-2015[14], which are provided in Equations. In other words, they are present in the same size as the other size. The stitching efficiency on a stitched image is evaluated in accordance with equations (7) and (8), respectively.

$$HSGV = \sum_{m=1}^{M} \sum_{n=1}^{N} \left| \widehat{I}(m,n+1) - \widehat{I}(m,n) \right|^2$$

$$VSGV = \sum_{m=1}^{M} \sum_{n=1}^{N} \left| \widehat{I}(m+1,n) - \widehat{I}(m,n) \right|^2$$

In comparison with current techniques such as brown and lowe, [2] and its versions like pair Euclidean and Minkowski distances the performance of the proposed mosaicing mechanism is compared. The results obtained on the image stitching are addressed here under ordinary circumstances, images with illumination variation.

B. Results in normal environmental condition

Fig. 1 demonstrates various techniques stitching performance in normal circumstances. Picture. 2(a) and (b) are images taken from various points, and in the figure 2 (c, d) the panoramic images developed from all mentioned methods are presented. Comparative evaluations of proposed and traditional stitching techniques, including the value for HSGV and VSGV as described by Morel and Guoshen-2011, FAST (Rosten and al-2010), the value of Euclides (Alahi et al., 2012) [23,12,1] are shown in Table 1. In addition to Euclidean distance based stitching, the proposed presented method achieved the maximum value of HSGV and VSGV and so on. Therefore, the proposed presented stitching ensures the overall first rank of all methods described in this paper that show the value of the stitched images.

Fig. 1. Results under normal environmental conditions, (a), (b) shows Images at different points, and Stitched image from methods based on (c) Euclidean distance, (d) Bound energy based matching.

Table 1: Stitching performance of various methods under normal conditions.

SGV

Similarity Method used	Image 1	Image 2	Average value	QUALITY LEVEL
Euclidean	344.1	74.1	209.1	4
ASIFT	338.1	89.07	213.585	2
FAST	322.3	96.56	209.43	3
FREAK	316	93.2	204.6	5
Bound energy	370	186.15	278.075	1

VSGV

Similarity Method used	Image 1	Image 2	Average value	QUALITY LEVEL
Euclidean	741.2	241.88	491.54	2
ASIFT	646.2	214.78	430.49	4
FAST	677.93	209.67	443.8	3
FREAK	624.8	198.76	411.78	5
Bound energy	789	226.9	507.95	1

C. Results Under illumination varying environment

For testing, the seamless stitching performance without any impact of light variation is assessed with two illumination modes together with the normal image. One of the two stitched images is subject to high lighting conditions to conduct such a survey, i.e. the White effect was introduced. The resulting stitched images are presented in the figure by four stitching techniques as shown in fig. 2. Sample images referred from [24] to develop panorama.

Fig. 2. Mosaicing results under illumination environment. Images to be stitched (a) noise-free image and (b) noisy image. Stitched image from methods based on (c) Euclidean distance, (d) Bound energy based matching.

Table 2 shows the results of stitching in the various lighting variation. Images to be taken (a) images that are under normal condition and (b) images that are under various illumination environmental conditions. Stitched results shows for methods relying on (c) Euclidean distance and (d) bound energy. The achievement of the stitching processes under different lighting impacts 1 and 2 for both HSGV and VSGV is shown in Table 2. The HSGV value for the suggested technique is greater under the illumination variation impact. However, it is evident from the rank estimate that the proposed technique gives viable stitching with an enhanced HSGV rating depending on the illumination variation impact image stitching. The maximum value for the proposed illumination variation condition bound energy method is higher value than Euclidean distance based stitching and other methods on a simultaneous basis. VSGV is also greater than other illumination impact techniques, which are handled by the suggested technique. In variable illumination effect, a VSGV score that is more than the VSGV valuation of Euclidean distance pairs of stitching as well as other techniques is achieved with a proposed technique. The increase in the HSGV and VSGV values at the start of the proposed image system with different illumination impacts demonstrate the effectiveness and perseverance of the sharpness perspective of the invariant stitchable variables.

TABLE 2: Mosaicing Results under Various Illumination conditions.

	HSGV				
Similarity measures	**ILLUMINATION EFFECT**	**IMAGE1**	**IMAGE2**	**Average Value**	**Quality Level**
Euclidean	1	588	143	365.5	3
	2	644	455	549.5	2
ASIFT	1	577	255	416	3
	2	591	488	539.5	2
FAST	1	530	143	336.5	4
	2	624	433	528.5	2
FREAK	1	566	344	455	2
	2	432	226	329	4
Bound energy	1	1112	134	623	1
	2	677	478	577.5	1
VSGV					
Similarity measures	**Illumination effect**	**Image 1**	**Image 2**	**Average Value**	**Quality Level**
Euclidean	1	1056	322	689	2
	2	1028	355	691.5	2
ASIFT	1	1023	350	686.5	2
	2	1033	336	684.5	2
FAST	1	1156	255	705.5	2
	2	788	322	555	3
FREAK	1	944	335	639.5	2
	2	566	322	444	4
Bound energy	1	988	501	744.5	1
	2	1145	388	766.5	1

V. CONCLUSION

Methods have been discussed for efficient image stitching. The gradient domain or the intensity domain can be used for image stitching. Here a brief summary of each of the two techniques developed by the nobles has been described. This paper provided a seamless image mosaicing system that works different lighting environmental conditions. The suggested mosaicing system is focused on the SIFT based image key feature matching which basically allows to overcome the scale, zooming and rotation impacts of stitching images. In the proposed framework, the RANSAC image key feature matching criteria is used for selecting the outliers and inliers depicting the dominant images with their important graphic visual content. In contrast with the known technique of Euclidean distance-based stitcher, the experimental findings of the proposed system are traditional image stitcher method and bound energy based mosaicing methods. The efficiency is calculated with the square gradient vertical and horizontal i.e. VSGV and HSGV. Experiment findings show that images can be analysed with noise environments with reduced misalignment or enhanced resolution under the proposed image stitching system.

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