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Feature-Based Stitching Algorithm of Multiple Overlapping Images from Unmanned Aerial Vehicle System

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Abstract *– This research presents a novel solution to cluster images from an Unmanned Aerial Vehicle System (UAV) using a feature-based stitching algorithm that employs a Binary Robust Invariant Scalable Keypoints (BRISK) feature detection technique. The UAV images are clustered by comparing the degree of overlaps, via the BRISK feature detection and matching, and a set threshold. The clustering serves as an essential solution in solving the stitching errors of UAV images, which are predominantly caused by inconsistent or overlapping regions. The Random Sample Consensus (RANSAC) is able to eliminate outliers on every paired keypoint and produces a precise computed homography or displacement of objects within images, thus making the stitching of multiple overlapping UAV images a success. Since the goal is to detect and cluster images qualified for image stitching. The aggregation of image smoothing is recommended. This will have a significant effect in eliminating minor problems such as the lack of color balance and seam presence, problems that slightly affect the visual appearance of the stitched UAV images.*

Keywords – Unmanned Aerial Vehicle System, Feature Detection and Matching, Image Clustering, Overlapping Region, Stitching Algorithm

INTRODUCTION

Photogrammetry is a subset of aerial photography defined as an art, discipline, and technology to obtain data and information about the physical environment through recording, measuring, and interpreting airborne photographs (also known as aerial images) [1]. This technology has been used in surveying and mapping Earth's land surface. It has various applications such as urban planning with high-quality maps, environmental management, disaster monitoring [2], and many others. The different platforms in aerial photography used for image acquisition are piloted-airplanes, satellites, and other flying objects.

Unmanned Aerial Vehicle (UAV) or commonly known as Unmanned Aircraft, or in a military terms called drone, on the other hand, is another type of platform which is remotely controlled by a pilot and can carry a camera with ultra-high resolution image settings [3] for aerial image acquisition. Accordingly, most photogrammetric mappings have used UAV in retrieving and recording geographic information compared to other platforms as mentioned earlier. This is because of the following reasons: 1) it flies in a low altitude flight, 2) it has high-resolution images, and 3) it has a low cost operating expense.

Nowadays, UAV has been successful in many areas due to its unique and reliable performance. In the agriculture sector, it is being utilized for precise agriculture to increase crop yields [4] and to have current monitoring on biophysical properties of different plants, weed productions, and pest and disease infestations. The said platform is also useful in flood monitoring and disaster damage evaluation especially in flood-affected Asian countries like Taiwan and China [5]. In a likewise manner, many wildlife ecologists throughout the world are now using UAV in wildlife monitoring and rangeland management.

Despite the merits, UAV have problems taking high-resolution images due to flight instability (caused by its lightweight feature) and a payload camera with a narrow field of view which can cover only limited surface of the land. Therefore, many applications on aerial imaging systems using UAV are obliged to perform image stitching as a resort on getting a broad view angle of the surveyed area to have a richly remotely-sensed visual information. However, the lateral degree of overlap between neighboring UAV images has always been the problem of image stitching. Subsequently, the selection of an appropriate matching technique (such as area-based or feature-based matching algorithms) used in analyzing the degree of overlaps also remained a challenge in most recent applications.

To circumvent the difficulties, some pre-processing of data should be done to guarantee that the images are qualified for stitching and mapping. In this paper, the researchers were able to employ an algorithm to overcome the said problem. The main functions are to cluster images that satisfy the overlapping requirement (via the identified threshold value) and to perform the stitching process in descending order (starting from the last picture).

In light of the study of [6] and [7], the researchers selected the feature-based matching algorithm known as Binary Robust Invariant Scalable Keypoints (BRISK) for the identification of the degree of overlaps on different UAV images which will also serve as the basis for image clustering. After clustering UAV images with ideal overlaps, the common stitching method for UAV images has been applied using the Random Sample Consensus (RANSAC) algorithm. The stitching process will use transformation matrix based on the matched features of clustered images which will be randomly collected (matched keypoint and outlier elimination) to calculate the homography for blending or combining pictures with ideal overlaps.

RELATED STUDIES

According to the study of *Peng Xiong et.al.* [8], the real-time image stitching on a battlefield using UAV was made possible due to their algorithm created based on predicted region matching. The pairing of every captured image was performed using the SURF feature matching technique to identify models that have identical features in its specific region. In their experiments, the said algorithm has found to be effective in reducing errors of stitching UAV images. However, the researchers suggested in finding the solution particularly on identifying images with the ideal overlaps to immediately identify candidates (a UAV image) qualified for image stitching.

Similarly, *Cheng Xing et.al.* [9] stated that analyzing the image overlaps will be much useful through down-sampling the resolution of images and choosing a simple descriptor or feature matching technique. The used of SIFT algorithm effectively analyzed the image overlaps and treated all wrong matching feature points, that yields to an encouraging results. The researchers achieved an effective and efficient overlap analysis because of the SIFT algorithm unique characteristics (such as invariant to scale, rotation, and mapping).

On the other hand, *Cheng Li et.al.* [10] framed a stitching algorithm for the sequential overlapping UAV images using feature points matching. The overlapping regions from the said images were being described using Oriented FAST and Rotated BRIEF (ORB) feature detection algorithm. Through the combination of ORB and Grid Motion Statistics, the researchers were able to cluster UAV images with identical overlaps and implemented a real-time image stitching.

THE ALGORITHM WORKFLOW

The researchers presents the different steps of the proposed algorithm through a workflow diagram as shown in Figure 1. These steps are explained thoroughly to understand the proposed algorithms further.

Step 1 is the process of comparing the base image ($Image_i$) with the succeeding image/s ($Image_{i+1}$) in a given dataset to determine the degree of overlap.

Step 2, the identification of the degree of overlaps between images is done using a BRISK algorithm. In particular, it uses unique feature detection and matching techniques which are necessary in analyzing image overlaps.

Step 3 will perform these sub-steps using BRISK:

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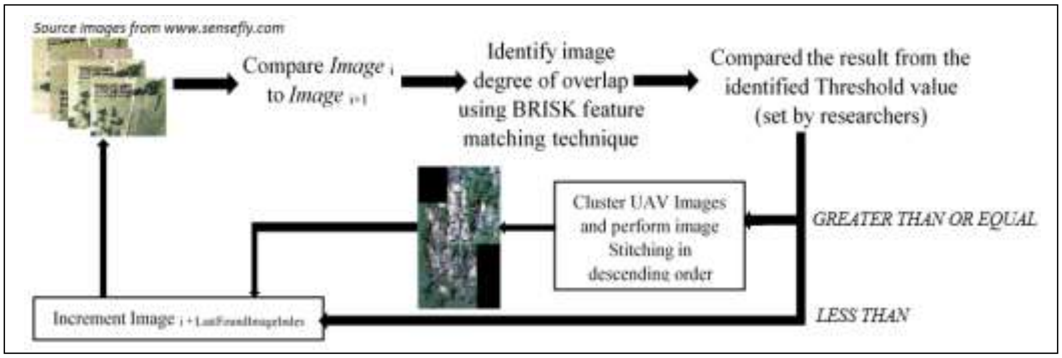

Figure 1. Algorithm Work Flow Diagram

(a) Matches = $M_{atch}\ K_{eypoint}\ (\ Img_{base}\ K_{eypoint}\ D_{istance}\ \&\ Img_{n+1}\ K_{eypoint}\ )$

(b) Good_match[] = $M_{atch}\ K_{eypoint}\ (\ Img_{base}\ K_{eypoint}\ D_{istance} < Img_{n+1}\ K_{eypoint}\ D_{istance}\ *\ 0.75\ )\ )$

(c) Decision = $(\ L_{ength}\ (\ Good\_match[]\ )\ /\ Matches\ ) >= T_{hreshold}\ (\ 3.0\ )\ )$

where *Matches* refer to the record of all unvalidated matched features between image A and image B using Brute-Force Hamming (B-F-H) distance technique.

On the other hand, *Good_match[]* are records containing all valid matched features (from images A and B) achieved by computing the distance of each feature point from the compared images as shown in sub-task (b). While in sub-task (c), a conditional statement on identifying Good Matched Keypoints with a value higher or equal to 3.0 (threshold value) was used in clustering UAV images with identical overlaps.

Step 4 is the process of stitching clustered UAV images in descending order. It is a standard method for image stitching which is able to maintain the quality of an image mosaic visual information.

```
Threshold is equal to 3.0
while i to numImages
    Images is equal to ListOfImages
    Accuracy = BRISKFeatureMatch(baseImage, ListOfImages)
    if Accuracy is greater than Threshold
        groupImages(ListOfImages)
FinalImage = stitch(groupImages[lastIndex-2],groupImages[lastIndex-1])
j = len(groupImages)
/*** Stitch UAV images with identical overlaps in Descending Order ***/
while j until 0
    stitch(groupImages[j],FinalImage)
    decrement j
```

Figure 2. Pseudocode on clustering and stitching UAV images

Figure 2 shows the pseudocode on the actual implementation of the proposed algorithm aggregating all the steps.

BRISK FEATURE DETECTION AND MATCHING

Keypoint Detection

In finding image keypoints, the Brisk algorithm uses the derivative of the FAST algorithm introduced by [11] in the year 2006. It identifies the unique location of objects that appear in an image through detection of corners, blobs, and T-junctions. Through a FAST algorithm, it will be able to detect every object's edge by analyzing the neighboring circular areas of every pixel *p* concerning its contrast as shown

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in Figure 3. It identifies all surrounding pixels that have higher intensity from every predicted region which makes it more effective compared to other well-known algorithms (such as SIFT and SURF) that uses blurring technique and requires a lot of computational power [12].

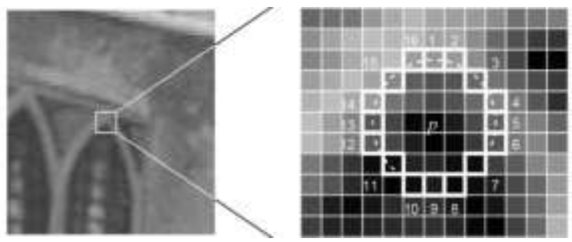

Figure 3. The FAST algorithm used in Keypoint Detection as illustrated by [11]

Keypoint Matching

The BRISK algorithm uses the long-distance pair calculation of every local gradient of pixels using Hamming distance through the given equation:

$$\mathbf{g}(\mathbf{p}_i, \mathbf{p}_j) = (\mathbf{p}_j - \mathbf{p}_i) \cdot \frac{I(\mathbf{p}_j, \sigma_j) - I(\mathbf{p}_i, \sigma_i)}{\|\mathbf{p}_j - \mathbf{p}_i\|^2}$$

where g is the gradient of every pixel p that contains the position of every identified keypoint. The intensity I serves as a crucial point on identifying edges of an object (see Figure 3). This process is able to help the researchers to list down all good matched vital points (from the compared UAV images) which are an essential parameter in clustering images with acceptable overlaps. Figure 4 shows the implementation of keypoint matching using the BRISK algorithm.

```
dm = cv2.DescriptorMatcher_create("BruteForce-Hamming")
matches = dm.knnMatch(des1,des2, 2)
matches_ = []
for m in matches:
    if len(m) == 2 and m[0].distance < m[1].distance * 0.75:
        print m[0].distance , m[1].distance * 0.75
        matches_.append((m[0].trainIdx, m[0].queryIdx))
```

Figure 4. Keypoint matching using BRISK

EXPERIMENTS

The different software used in the creation of the various modules are OPENCV2 and PYTHON2 with a 2.7 version. The recommended hardware specification is the following: Intel(R) Core(TM) i7-8750 CPU @ 2.20 GHz, 6 MB Cache, and 8.00 GB RAM.

The researchers gathered datasets from known websites which offered free download of UAV images for research. The dataset A contains more than 200 images which were acquired from the website www.sensefly.com, while dataset B contains five images from the website www.kushalvyas.com, a GitHub project, and dataset C contains 42 images which were collected from the website www.dronemapper.com.

The primary purpose of the experiments is to assess the effectiveness of the algorithm in identifying the unmanned aerial vehicle (UAV) images that are eligible for image stitching based on their overlaps. Different stitching errors, which are predominantly caused by inconsistent or overlapping regions on the said platform, are prevalent problems in aerial photogrammetry. Therefore, in order to determine the algorithm's functionality, the researchers selected five images from every dataset to be processed and evaluated based on criteria, such as keypoint detection, keypoint matching, clustering of images with ideal overlaps for multiple image stitching, and comprehensive visual information of stitched images. These are shown in Figures 5, 6, and 7.

Table 1 shows an example of the detailed results of stitching multiple overlapping UAV images without the proposed algorithm. The image stitching produced the unclustered and poor quality stitched images from the experiments conducted by the researchers on the three datasets. Figure 6 depicts the poor quality visual information on stitched images due to the absence of the feature-based stitching algorithm which corresponds to the given results shown in Table 1.

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Table 1. Clustering and Stitching UAV images using BRISK without the Proposed Algorithm

Dataset	Total Images	Cluster(s)	Stitched Images	Unstitched
A	5	0	*Poor Quality Image*	0
B	5	0		
C	5	0		

Table 2 shows an example of the detailed results on image keypoint detection and matching, where each of the identified values on variables M and GM (refers to the algorithm Step 3) will be processed in gauging each of UAV image degree of overlaps. This is considered as the vital process in clustering images with an ideal overlapping region.

Table 2. Keypoints detection and matching for overlap identification using BRISK

Dataset	Total Images	Matches (M)	Good Match (GM)	Degree Overlaps (GM/G)
A	2	660	207	31.36
B	2	4713	231	4.90
C	2	3697	572	15.47

Figure 5 displays the consistency of a BRISK algorithm in identifying and matching keypoints in three datasets. The algorithm provides sufficient detection of the degree of overlaps relevant for clustering UAV images.

Table 3 shows an example of the results of the different number of clusters per dataset, after identifying the degree of overlaps of different matched UAV images which was higher or equal to the set threshold value. As a result, each of the clustered images was stitched together completely as displayed in Figure 7.

Table 3. Clustering and Stitching UAV images with ideal overlaps using BRISK and the Proposed Algorithm

Dataset	Total Images	Cluster(s) ID	Stitched Images	Un-stitched	Total %
A	5	A1	3	0	100
		A2	2	0	100
B	5	B1	3	0	100
		B2	2	0	100
C	5	C1	2	1	80
		C2	2		

Figure 7 demonstrates that the proposed algorithm effectively created a clustering of images from its total sample size in all three datasets. Due to the positive result, stitching of multiple overlapping images from the UAV system produced a good result by stitching images with ideal overlaps in descending order.

Overall, this research on the feature-based stitching algorithm of overlapping images from the UAV system yields a positive result through clustering and stitching multiple overlapping images. The findings of this research might contribute to the body of knowledge related to aerial photogrammetry.

CONCLUSION

A new algorithm proposed in this paper answered the problem of stitching UAV images with inconsistent overlaps. The novel solution of clustering every image in the dataset produced significant contributions in the whole stitching process, notably eliminating errors like low-quality visual information, which are prevalent in the most aerial imaging system. With the series of experiments, the proposed method consistently performed image clustering using BRISK (feature identification and matching) and RANSAC (eliminating keypoints outliers and computing the appropriate homography) algorithms. This research provides a new avenue to solve a problem in many applications related to image stitching. The recommendation is the inclusion of the smoothing process to remove minor faults like no-color balance and seam appearance which somewhat affects the visual information of the stitched UAV images.

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Figures

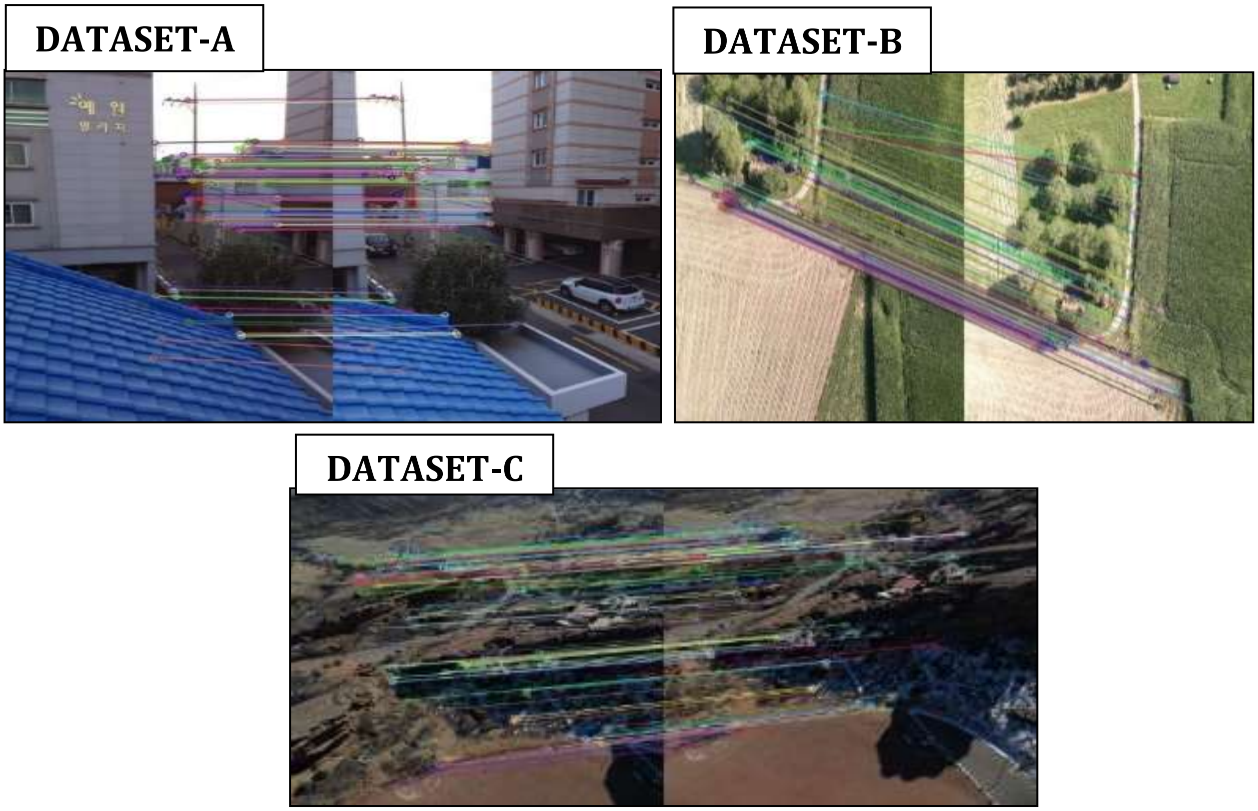

Figure 5. Keypoint Detection and Matching using BRISK

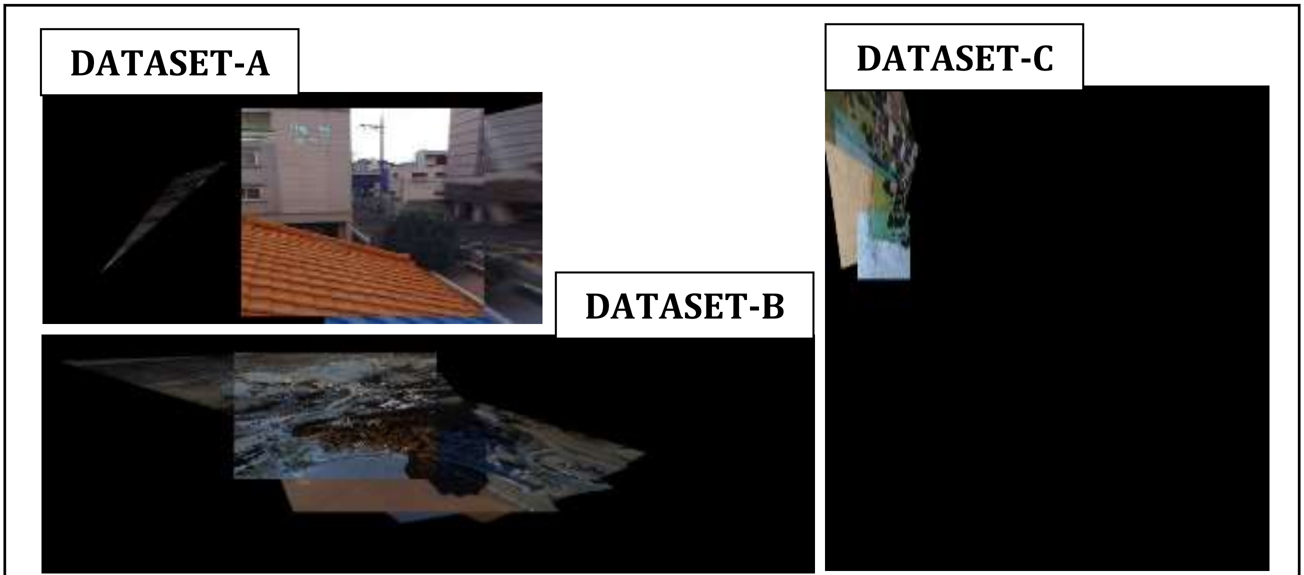

Figure 6. Image Stitching using BRISK without the Proposed Algorithm

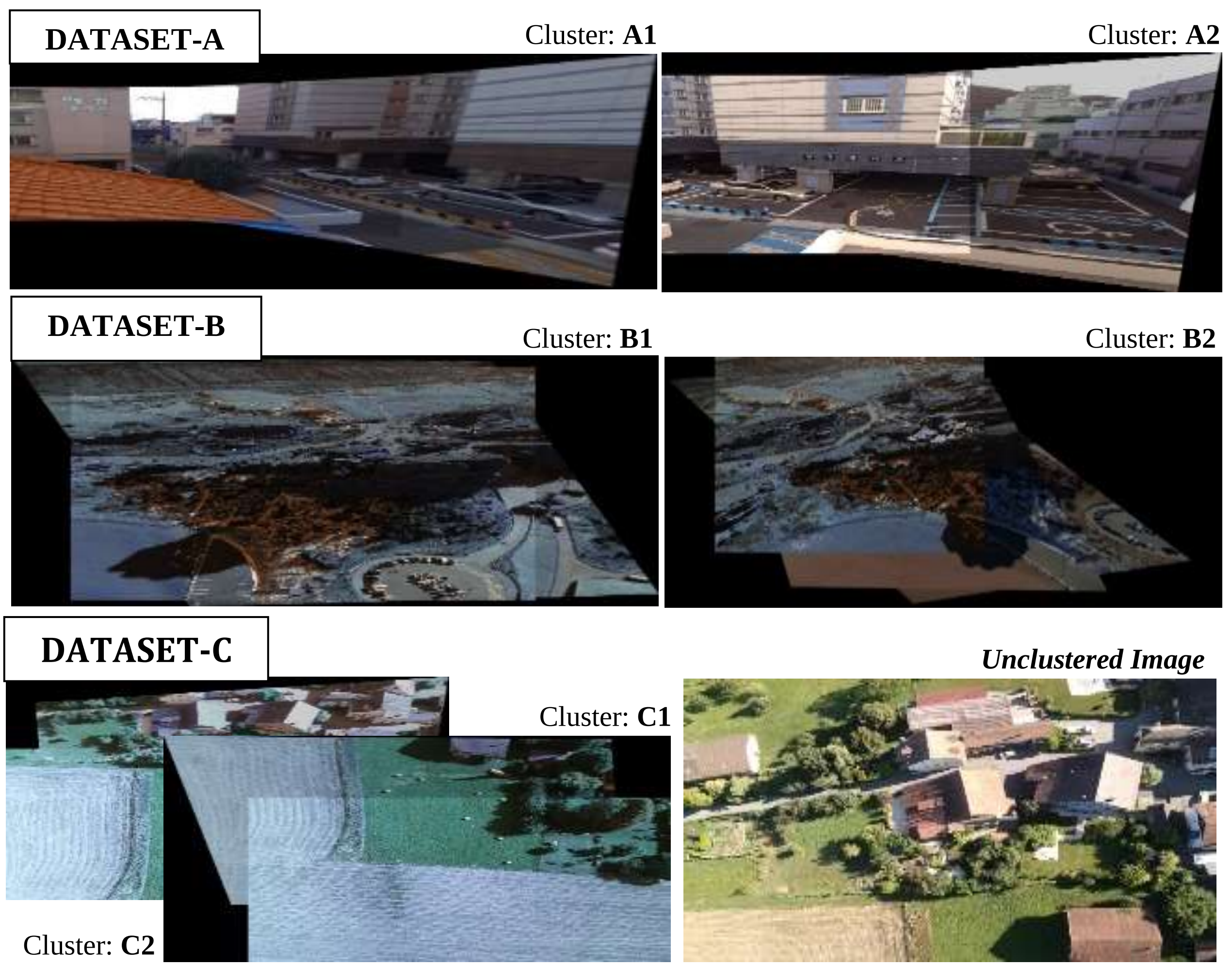

Figure 7. Image Stitching using BRISK and the Proposed Algorithm