

## OBJECT-BASED CHANGE DETECTION USING GEOREFERENCED UAV IMAGES

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### ABSTRACT

Unmanned aerial vehicles (UAV) have been widely used to capture and down-link real-time videos/images. However, their role as a low-cost airborne platform for capturing high-resolution, geo-referenced still imagery has not been fully utilized. The images obtained from UAV are advantageous over remote sensing images as they can be obtained at a low cost and potentially no risk to human life. However, these images are distorted due to the noise generated by the rotary wings which limits the usefulness of such images. One potential application of such images is to detect changes between the images of the same area which are collected over time. Change detection is of widespread interest due to a large number of applications, including surveillance and civil infrastructure. Although UAVs can provide images with high resolution in a portable and easy way, such images only cover small parts of the entire field of interest and are often with high deformation. Until now, there is not much application of change detection for UAV images. Also the traditional pixel-based change detection method does not give satisfactory results for such images.

In this paper, we have proposed a novel object-based method for change detection using UAV images which can overcome the effect of deformation and can fully utilize the high resolution capability of UAV images. The developed method can be divided into five main blocks: pre-processing, image matching, image segmentation and feature extraction, change detection and accuracy evaluation. The pre-processing step is further divided into two sub-steps: the first sub-step is to geometrically correct the bi-temporal image based on the geo-reference information (GPS/INS) installed on the UAV system, and the second sub-step is the radiometric normalization using a histogram method. The image matching block uses the well-known scale-invariant feature transform (SIFT) algorithm to match the same areas in the images and then resample them. The image segmentation and feature extraction block is used to separate the images to different meaningful regions by the mean shift method, extract the textural features and contextual features (polygon, etc.), Based on the features extracted above as well as the SIFT features of the area, the optimization result is achieved by considering the neighbourhood information. The proposed method is being tested by using multi-temporal images acquired by UAV. The results confirm the effectiveness of the proposed approach.

### 1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have many advantages over traditional manned aircrafts or some other remote sensor platforms. For example, UAVs are low cost platforms and can work without consideration of human factors by using an auto-remote control flight mode. They can be easily implemented for high-risk and high-tech missions and do not require permission from airspace control for low-altitude flights in most countries. UAVs can also provide high resolution images and precise positioning/orientation data from the on board GPS/GNSS and INS navigation sensors. These characteristics enable the UAV platform to be an effective supplement way to the traditional satellite and manned-plane remote sensing.

Although the UAVs can provide images with high resolution in a portable and easy way, their role as a low-cost airborne platform for capturing high-resolution, geo-referenced still imagery has not been fully utilized. One potential application of such images is the ability to detect changes between images of the same area over time.

Change detection is of widespread interest due to a large number of applications including surveillance and civil infrastructure. Until now, there are not many applications of change detection for UAV images. This is due to the fact that UAV images are often distorted due to the noise generated by the rotary wings, which makes it difficult to analyse such imagery, and also the images only cover small parts of the interesting areas. Therefore an automated method capable of managing large data is of potential benefit.

As mentioned in the literature, to obtain as high as 90% precision in change detection, the precision of geometric registration of imagery should be higher than 0.22 pixels (Zhong 2006). This is very difficult to obtain from UAV images as the UAV images are highly deformed due to the rotary wings noise. Despite the presence of such issues, the use of UAV sensors in change detection is potentially attractive from the operational viewpoint, as they can provide images with high resolution. Until now, there is not much application of change detection for UAV images. Also the traditional pixel-based change detection method does not give satisfactory results for such images as most of the traditional methods have high demand of accuracy on registration whereas only few studies have addressed the description of the fully automatic change detection methods for images with high resolution and high deformation (Celik, 2009a; Pacifici *et al.*, 2007; Pacifici and Del Frate, 2010)

According to the strength and weakness of UAV images, several issues have to be specifically considered. The crucial ones include possible mis-registrations (that leads to double lines in difference image), shadow and other seasonal and meteorological effects which add up and are combined to reduce the attainable accuracy in the change detection results. So an appropriate approach to take these issues into account could be to emphasize the pixel contextual information, which can make full use of the high resolution and offset the deformation. Such similar approach was indeed proposed in (Pacific *et al.*, 2007), who made a progressive use of pulse-coupled neural network algorithms for the extraction of changed information after change vector analysis (CVA) and (Bruzzone, 2010) developed an approach to reduce the effects of registration noise in unsupervised change detection by estimating the distribution of the registration noise. Although these methods work in some situations, but suffer from bigger registration errors.

To overcome the effect of deformation and to fully utilize the high resolution capability of UAV images, in this paper we have proposed a novel object-based method for change detection with UAV images. The key point is to integrate the contexture information by the mean shift algorithm to the initial change detection method, which can overcome the noise of the registration and greatly improve the result.

The paper is organized as follows. Section II describes the preprocessing of UAV data. The proposed unsupervised change detection approach is presented in Section III. Section IV provides experimental results of the proposed approach for the ground truth data and comparisons with the traditional well used methods proposed by Celik *et al.* (2009). Section V gives the concluding remarks.

## 2. UAV data pre-processing

Images acquired at different times usually have different amounts of haze and dust in the atmosphere and are with different geo-referenced data sets. Before the differences between images can be computed, one has to make sure that the images maintain similar illumination standard (namely atmospheric correction) and with little deformation as possible (namely geometric correction), and also the two images should be aligned properly (namely image registration). These form the basis of pre-processing step which includes: atmospheric

correction and image rectification (geo-referencing) which will offer the basic data for change detection to be discussed below:

### 2.1 Atmospheric correction for UAV images

This is to correct for factors such as scene illumination, azimuth, elevation and weather condition such as (strong sunshine, cloud). Various practical algorithms are available to remove atmospheric effects. As our goal is to get the difference between images, to simplify the process, the relative atmospheric correction method is well suited for our case. In such method, only one of the images is adjusted according to the other image. Based on the assumption that surface reflectance histograms of the similar regions are the same, the other image is shifted to match the histogram of their reflectance of the first regions.

### 2.2 Geometric correction for UAV data

Geometric correction can be performed using parametric or non-parametric approaches. Non-parametric approaches require the identification of features common to the sensed image and a map. Conventionally, the distinct point-like features termed ground control points (GCPs) are used. Parametric approaches require information concerning the sensing geometry and the sensor exterior orientation parameters (attitude and position) which describe the circumstances that produced the sensed image (Downman *et al.* 1984), as the exterior orientation parameter is already provided indirectly by the INS system, in this paper, the parametric approach is concerned for geometric correction.

INS (Inertial navigation system) installed in the platform determines the attitude when acquire the images, which is defined in terms of pitch, roll, and yaw rotations about the device axes  $x$ ,  $y$ , and  $z$  respectively. These can be expressed as a single device attitude matrix (namely exterior orientation elements in photogrammetry) by applying rotations in a specific order around the device axes. The device attitude rotation matrix is defined (equation 1) by application of a yaw rotation about the yaw axis followed by a pitch rotation around the once displaced pitch axis followed by a roll rotation around the twice displaced roll axis (Thompson 1969).

$$A = \begin{pmatrix} \cos(y)\cos(r) - \sin(y)\sin(p)\sin(r) & -\sin(y)\cos(p) & \cos(y)\sin(r) + \sin(y)\sin(p)\cos(r) \\ \sin(y)\cos(r) + \cos(y)\sin(p)\sin(r) & \cos(y)\cos(p) & \sin(y)\sin(r) - \cos(y)\sin(p)\cos(r) \\ -\cos(p)\sin(r) & \sin(p) & \cos(p)\cos(r) \end{pmatrix} \quad (1)$$

in which A is the exterior orientation measurement attitude matrix;  $y$  is the yaw angle;  $p$  is the pitch angle; and  $r$  is the roll angle. In this way, the geometric transformation can be carried out between two non-orthonormal co-planar frames with different origins and non-parallel basis vectors .

### 2.3 UAV image registration

There are many scale and rotation invariant feature extraction algorithms for image matching that have been proposed such as: Scale invariant Feature Transformation (SIFT) (Lowe, 2004), and Speeded up robust features (SURF) (Bay, 2006). In this paper, the SIFT algorithm was chosen to extract the features from the images as it is more stable and can match with higher accuracy. After the set of feature points are extracted using the SIFT algorithm, then the match step can be done by comparing

the minimum Euclidean distance between the extraction feature vector, and then compute the relationship between two images. Finally the two images are registered by the projection transformation. It is noted that the sift matching feature on the reference images will then combine the segmentation algorithm and the initial result generated by the commonly used change detection method to optimize the result in the next section.

### 3. The Proposed change detection method

Now we suppose two UAV images acquired at the same geographical location but at different times  $t_1$  and  $t_2$  have been registered based on the pre-processing introduced in Section II. The Workflow of our proposed method is illustrated in Figure.1. This method mainly consists of three stages, namely, initial change map generation based on the Principal Component Analysis and k-Means Clustering; optimize the result by combination of Meanshift segmentation and SIFT feature, which are introduced as follows in detail.

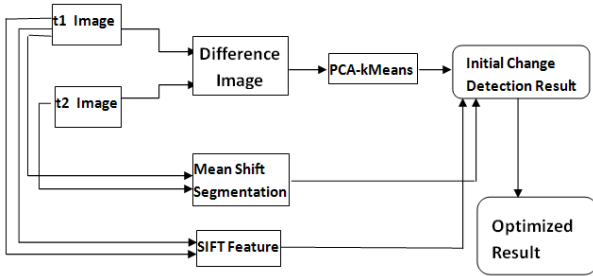


Figure. 1. Workflow of the proposed approach.

#### 3.1 The initial change detection result based on Principal Component Analysis and k-Means Clustering

The change detection method focuses on how to incorporate the object information to initial change detection result based on the difference images, in this paper, we employ the simple and commonly used PCA-kMeans technique proposed by Celik (2009a) to get the initial change detection result. The main idea is described as follow:

First, the difference image  $X_d$  of two UAV images is acquired from the same area coverage;

$$X_d = |X_1 - X_2|$$

Second, the non-overlapping blocks of the difference image are used to extract eigenvectors by applying PCA (Gonzalez and Woods, 2006);

Third, a feature vector for each pixel of the difference image is extracted by projecting its  $h \times h$  neighbourhood data onto eigenvector space. The feature vector space is classified into two classes by k-means algorithm (Gonzalez, 2006). Each class is represented with a mean feature vector.

Finally, an initial binary change map  $X_{mi-CM}$  is achieved by assigning each pixel of the difference image to one of the class according to the minimum Euclidean distance between the pixel's feature vector and mean feature vector of the class (Celik, 2009b), in which '0' indicates that the corresponding pixel has no change, whereas "1" indicates that involving a change case, i.e.,

$$X_{mi-CM}(i, j) = \begin{cases} 0, & (i, j) \in \text{unchange area} \\ 1, & (i, j) \in \text{change area} \end{cases} \quad (2)$$

The use of large value of  $h$  results in an increase of miss-detections. In our case, we used the lowest value of  $h = 2$  in order to avoid mis-detection which may lead to false detections which can be overcome in the segmentation step. Our focus here is to ensure that there are no missed change detection polygons.

#### 3.2 Feature combination for producing the optimized change-detection map

##### 3.2.1 Mean shift segmentation

The goal of segmentation is to simplify the representation of an image into something that is more meaningful or easier to analyze. In another word, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. In this paper, the Mean Shift algorithm is chosen to get the segmentation result.

The Mean Shift algorithm is applied for image segmentation (Comaniciu, 2002), which is a nonparametric clustering technique based on an iterative scheme to detect modes in a probability density function. There are no assumptions about probability distributions, and all the pixels that shift to the same peak are considered to have the same class based on the feature space composed of both spatial and color information.

Let  $x_i = 1, 2, \dots, n$ , be the  $n$ -dimensional input image pixels in the spatial (the coordinate in the image) and range (the value of pixel) domain, and the mean shift is:

$$m_h(x) = \frac{\sum_{i=1}^n x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^n g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x \quad (3)$$

where

$$g(y) = \begin{cases} 1-y, & \text{if } |y| \leq 1 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$y = \left\|\frac{x-x_i}{h}\right\|^2 \quad (5)$$

The segmentation result is affected by many factors such as homogeneity of images, spatial structure character of the image, continuity, texture, image content, physical visual, etc. (Bay, and Tuytelaars, 2006).

##### 3.2.2 SIFT features and mean shift segmentation to optimize the initial result

After segmented by mean shift algorithm, the images are

divided into different regions which is namely objects. To be more intuitive, the segmentation result will be showed in the form of binary edge image.

Normally, regarding the change detection result based on the analysis of the difference image, the registration noise resulted from distortion between UAV images mostly shows in the way that the no perfect alignment edge, which means the mis-judged change may most likely happen in the boundary of the images, so we put our focus on how to remove this kind of main misjudged change (pseudo change). The scheme of the removing the mis-judged change area is showed in Figure 2.

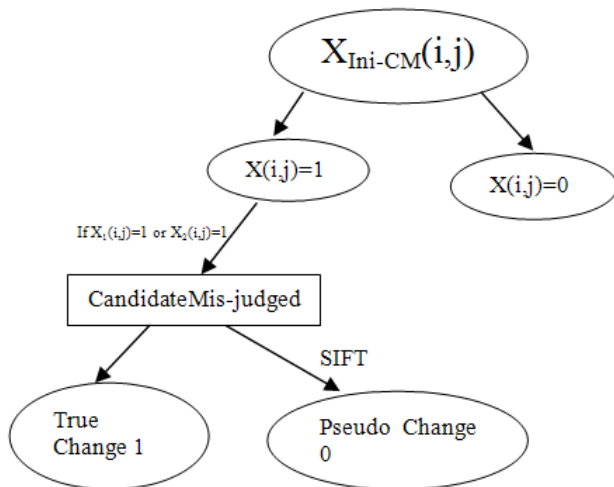


Figure 2 The scheme of the removing the mis-judged change

Based on the segmentation result in the form of edge image, firstly, the candidate mis-judged change area is identified, if the changed pixel on the initial change detection result locate either or in the boundary of t1 segmentation image or t2 segmentation image, we say this pixel is the candidate mis-judged change area.

Secondly, discriminate the pseudo change and true change on the candidate misjudged change area. As the SIFT feature is the oriented gradient that exist near the boundary with sharp intensity change, we can make full use of this characteristic to remove the mis-judged change pixel. In our images, the registration accuracy is 0.5 pixels, so a search radius of 1 pixel is used. To simplify the process, we define the 8-neighborhood (Figure 3). After get the corresponding matching SIFT features between the two images, if there is one or more SIFT feature in the 8-neighborhood of the candidate misjudged change area, which implies that this pixel is pseudo change, namely, in the final change detection result, the value of this pixel is 0, otherwise it is considered as true change, in the binary image, which means the value of the pixel is 1,

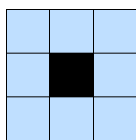


Figure. 3 8-neighborhood data for a pixel

In this way, some of the misjudged pixels caused by mis-registration or some other noise mentioned above are removed.

#### 4. EXPERIMENTAL RESULTS

In order to assess the effectiveness of the proposed approach, we considered a real data set taken from UAV. The data (Figure 4) is composed of 850\*736 pixels (1m resolution) of the same area in Guangzhou, China at different times. Figure 5 shows the result using the pre-processing introduced in Section 2 above. The matching result containing the SIFT feature are given in Figure 6.



Figure 4. UAV images taken at different times



Figure 5. Two UAV images after preprocessing

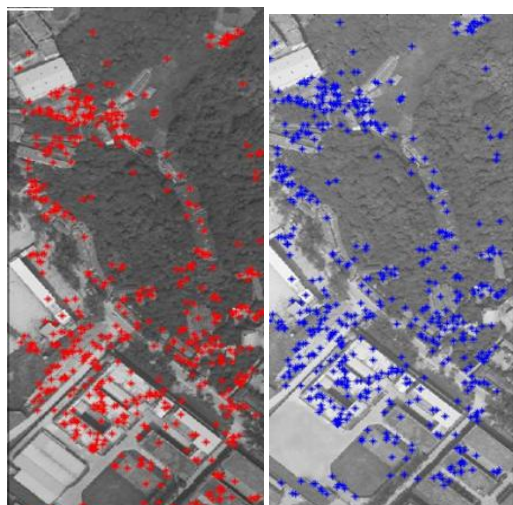


Figure 6. SIFT features extracted from the two images

It can be clearly seen that all the SIFT features are close to the edge. The combined SIFT features with segmentation algorithm are given in Figure 7(a) and the initial result based on the PCA-Kmeans approach is shown in Figure 7 (b). Next the mis-judged polygons were detected based on the proposed approach and is highlighted in Figure 8(a). The final change detection result is given in Figure 8(b). Compared to Figure 7(b), it can be seen that the misjudged changes are improved by the proposed combination method, which reduces the mis-registration and can detect the noise. However, there are still some errors due to the shade of the UAV images that cannot be removed. Overall, the final result show the proposed methods has potential benefit for the automatic change detection in UAV images, despite the fact that the two images are co-registered without high accuracy.

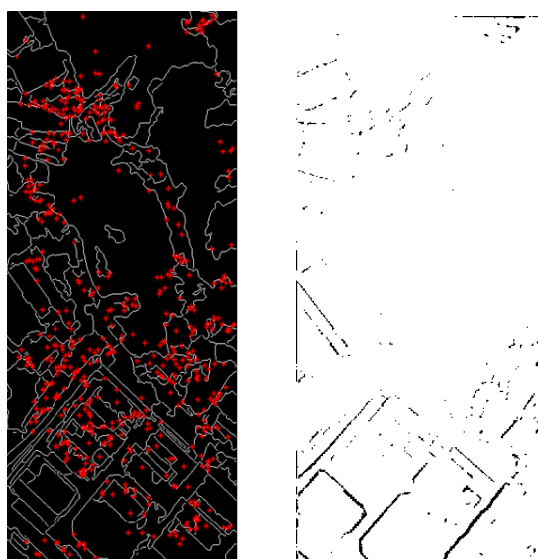


Figure 7. (a) The combined SIFT features with segmentation algorithm, (b) Change detection result based on the PCA-Kmeans method only.

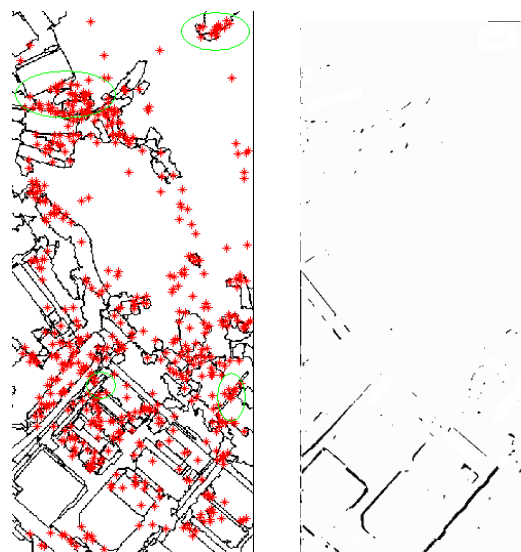


Figure 8. (a) Midjudged polygons based on the proposed approach, (b) the optimized change detection result.

## 5. CONCLUSION

In this paper, an object-based change detection by combing the segmentation information and SIFT features has been developed, which can overcome the relative big registration error caused by the bigger UAV rotation angle when captured the UAV images, as the contextual neighborhood information, especial boundary has been taken into account in the change detection process. The results showed the potential benefit in case of UAV image use. But the result has some restrictions to the segmentation, so future work will focus on efficiency of the segmentation method, also some pre-processing should be considered to avoid the shade effect.

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