Rapid Processing of Unmanned Aerial Vehicles Imagery for Disaster Management

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SUMMARY

The use of Unmanned Aerial Vehicles (UAVs) in civilian applications has increased greatly over the last few years. Especially for small area coverage, such a system has the advantages of being more flexible, rapid, efficient, and weather independent when compared to standard airborne aerial surveys. Of high interest is their application in the acquisition of aerial imagery for post-disaster assessment where accessibility to current and accurate spatial information is critical for the effective response to a crisis by the relevant agencies.

This use of UAVs calls for near-real time processing of the images to create orthophoto mosaics. However, many commercial systems are incapable of performing automatic image matching on UAV imagery due to the high variability present in the image scenes. This paper presents a method for the automatic generation of orthophoto mosaics using Scale Invariant Feature Transform (SIFT) approach for the automatic keypoint detection and matching problem. The proposed workflow makes use of efficient and robust algorithms to achieve a method that will meet the needs of the near real-time requirements.

The results of this paper demonstrate a suitable approach to the automated processing of UAV images and further promote the applicability of this technology to the acquisition of geospatial data for natural hazard and disaster management.

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1. INTRODUCTION

The civilian use of unmanned aerial vehicles (UAV) is expanding rapidly. UAVs are the fastest growing sector in the aerospace market, over the last 5 years their production has more than doubled while civilian and research applications have grown threefold and twofold respectively (UAV International 2010). There are now many companies dedicated to the production of fixed and rotary wing UAV specifically designed for civilian applications such as agriculture, forestry, security and aerial surveillance.

This popularity is in most part due to their ability to perform multi-temporal spatial data acquisition at a low cost with flexible and rapid deployment. UAV also provide the opportunity for new applications in close range aerial photography and photogrammetry (Eisenbeiβ 2009). These attributes make UAV photogrammetry and remote sensing (P&RS) an attractive alternative to traditional applications of aerial data collection.

One such area of application which is gaining interest is the use of UAV P&RS for disaster mapping and management (Bendea et al. 2008; Al-Tahir et al. 2011). Disaster mapping is the process by which data concerning the spatial distribution of the impacts of natural and manmade disasters is acquired, processed and presented. It can convey information regarding the spatial location of a disaster as well as the spread of or probable effects relating to a disaster (Jena 2003). Following the disaster occurrence data acquisition becomes critical in planning and executing the response action. The main requirements for the data acquisition are real time/rapid processing, multi temporal resolution and high spatial resolution. In addition to the operational requirements this also necessitates the need for speedy automated processing techniques.

Orthomosaics are among the most common aerial data products utilized in disaster management. The creation of these mosaics requires the orientation, matching and stitching of many photographs together to produce a photographic recreation of the entire surveyed scene. The methodologies for performing these processes are well established for traditional photogrammetry and automatic aerial triangulation (AAT) has actually become a standard process.

The AAT of the small format images acquired from UAV however presents a processing challenge due to the highly variable nature of these digital images. The light-weight construction of small UAV leads to instability in the flight trajectory causing large rotation angles and variable camera perspectives while the low operational altitude and small image footprint result in large scale differences, occlusions and sometimes strong illumination changes between frames. The commercial AAT systems are unable to handle the large variances in these images and as a result many of the automated processes such as tie-point extraction have to be performed manually. While manual tie-point extraction can be used in some instances it becomes impractical for large volumes of photographs as it is too laborious and expensive to perform. In addition it will not meet the requirements of near real-time or rapid processing.

There has been a wave of new research in an effort to standardize workflows for the processing of UAV imagery and to adopt more automated and rapid processing techniques as are common in traditional photogrammetry. These new techniques involve the use of tie point extraction algorithms which utilize scale invariant features within the image scenes. Scale invariant feature extraction and matching are commonly utilized in computer vision applications utilizing feature extraction algorithms such as Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Feature (SURF) (Herbert Bay et al. 2008). This paper will seek to examine these algorithms and apply them in proposing a specific methodology for the processing of UAV images for real-time/rapid orthomosaic generation.

2. FEATURE EXTRACTION AND IMAGE MATCHING

2.1 Image Matching

Image matching is fundamental to the process of orthomosaic generation. There are two primary methods employed in image matching, these are Correlation Based and Feature Based Matching. Correlation Based Template Matching approaches involve the matching of an image region across all locations of the image space. This approach is very computationally expensive and therefore not suitable for real-time and rapid processing applications. In addition these methods are not robust and challenges arise when there is significant variability in rotation, scale and illumination in the images.

Feature Based Matching is an alternative matching approach involving the extraction and matching of distinctive image features such as edges and corners. These features are used to determine the relative orientation of image pairs by correlating only these features within the image spaces. This results in a faster computation as the matching is more localized. However, in some cases these methods do not extract sufficient or stable enough features to allow robust matching (Lowe 1999).

Many of the current commercial systems employed for image matching of aerial imagery depends on one of these afore-mentioned methods. The result is their inability to efficiently and accurately perform automatic keypoint extraction on images acquired from low altitude UAV (Eisenbeiβ 2009).

2.2 SIFT Feature Based Matching

Lowe (2004), presents a method for the extraction of distinctive features from images called the Scale Invariant Feature Transform (SIFT). The method is so called due to its ability to transform image data into localized scale-invariant features. These features are invariant not only to scale but rotations and partially invariant to illumination changes and camera perspectives. These characteristics make the SIFT features suitable for the matching problem of UAV imagery and new approaches are being explored for their use in AAT (Bazaretti et al. 2010; Bendea et al. 2008).

In addition to its robustness to image variability the SIFT method is also well suited for real-time processing as it adopts an image pyramid approach to the computation process. This ensures that the more expensive computations are only performed at selected candidate locations.

2.2.1 Feature Extraction

The generation of SIFT features comprises of four phases: Scale Space Extrema Detection, Keypoint Localization, Orientation Assignment and Keypoint Description. Scale Space Extrema Detection (Lindeberg 1993) is the first step and is directly responsible for the ability of SIFT to detect features invariant of scale. It involves the construction of a scale space of the image. The scale space is defined as a function, $L(x,y,\sigma)$ which is produced from the convolution of a multi-scale Gaussian filter, $G(x,y,\sigma)$ over an image, $I(x, y)$:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y), \tag{1}$$

where $*$ is the convolution operation in x and y , and

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \tag{2}$$

Keypoints are then detected using the efficient difference-of-Gaussian function, which is easily computed by differencing two adjacent scales. Keypoints are located at the local maxima and minima and are detected by comparing each sample point to its surrounding neighbors in the selected scale space and adjacent scale spaces.

Keypoints are localized by fitting candidates to a detailed model in order to determine their scale and location. The Taylor expansion is used to determine the interpolated location of the keypoints. Points which are located on edges or which have low contrast are rejected at this stage to increase stability and matching performance.

SIFT keypoints achieve rotation invariance by assigning a consistent orientation at each keypoint which then acts as a baseline for which the keypoint descriptor is relatively oriented to. For each sample, $L(x,y)$ at the selected scale, the gradient magnitude, $m(x,y)$, and orientation, $\theta(x,y)$, are calculated.

The previously measured parameters are then assigned to a distinctive feature descriptor. This is performed by finding the local image gradients of the keypoint region at the selected scale. The gradients are then distributed into orientation histograms composed of 8 bins over a 4x4 region. The descriptor is finally formed by transforming the values of the histograms into a 128 element vector and normalized to reduce the effects of illumination variance.

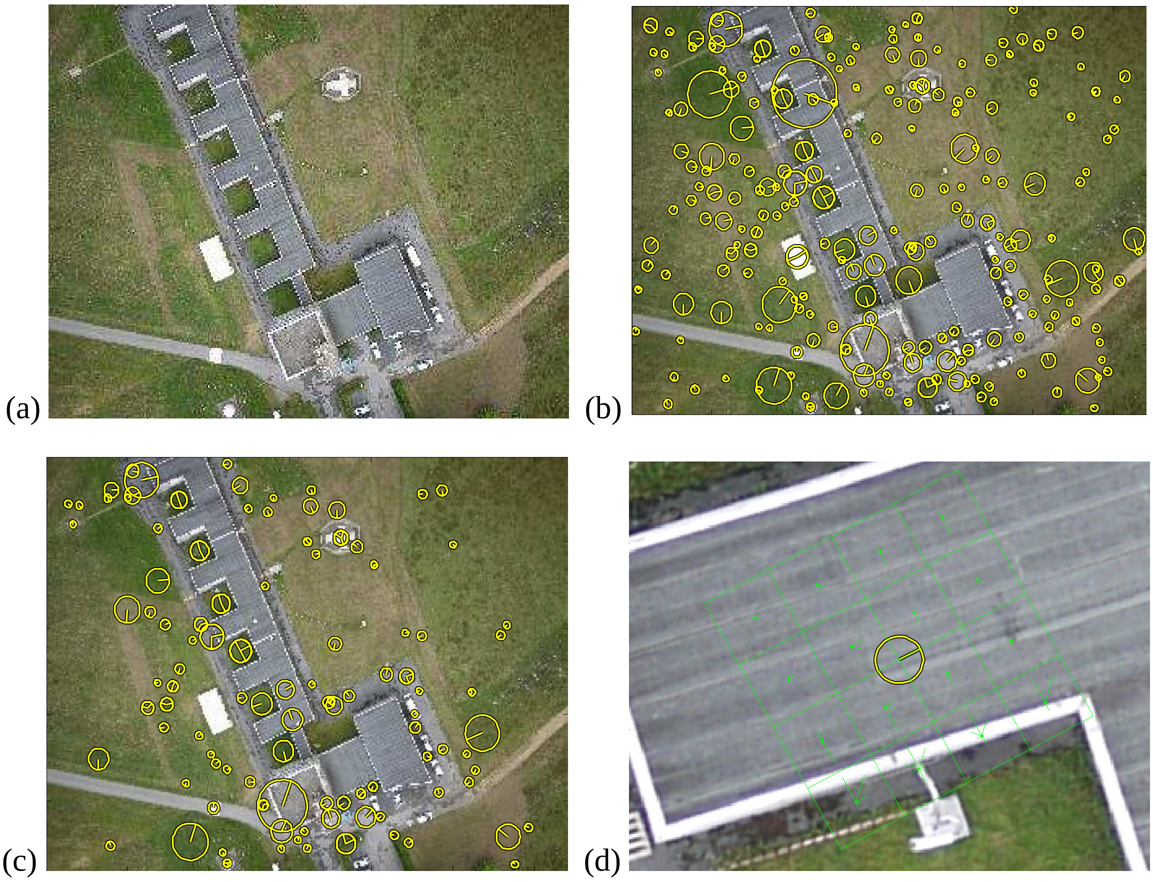
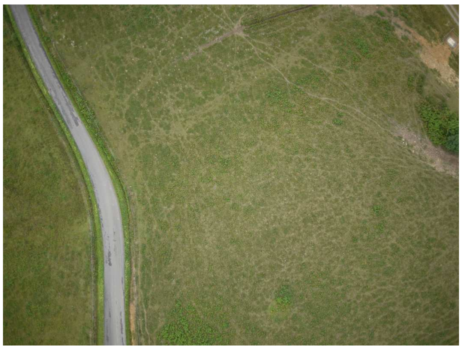
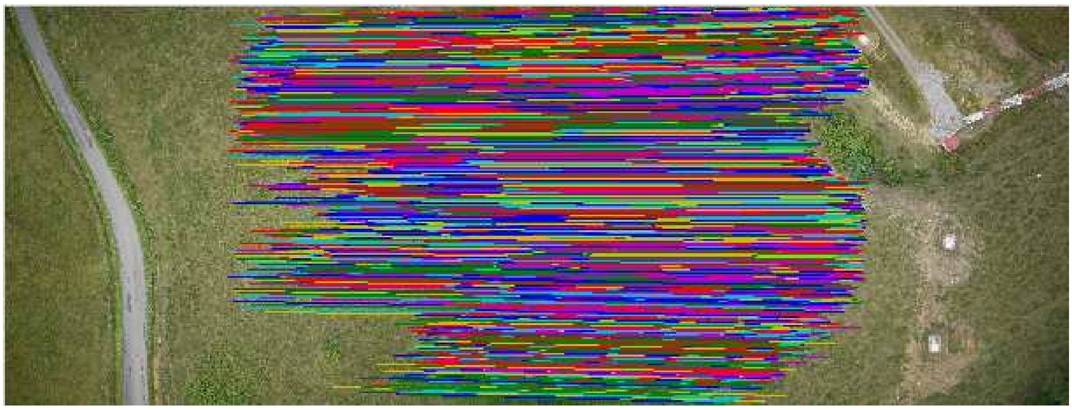


Figure 1. SIFT keypoint frame and descriptor extraction. (a) Original image 320 x 240 (b) 267 frames detected in the initial run (c) Framess reduced to 125 by applying peak and edge thresholds (d) an example SIFT frame (yellow) and descriptor (green) representation, each frame has a location, scale (represented by frame radius) and rotation.

2.2.2 Feature Matching

The next step after feature extraction is feature matching. This involves matching the keypoints within the images among a set of generated image pairs. Best matching candidates are found by identifying nearest neighbors as defined by the keypoints with minimum Euclidean distance between the SIFT descriptor vector. This type of search is exhaustive and inefficient for such high dimensional spaces and so an approximation, Best-Bin-First (BBF) [9], to the nearest neighbor is used instead. BBF algorithm is a modified version of the k-d tree algorithm where the search ordering is performed in order of closest distance to the query site. Other matching methods include RANdom Sample Consensus (RANSAC), Least Median of Squares and the Hough transform (Hough 1962).

(a)  (b) 

(c) 

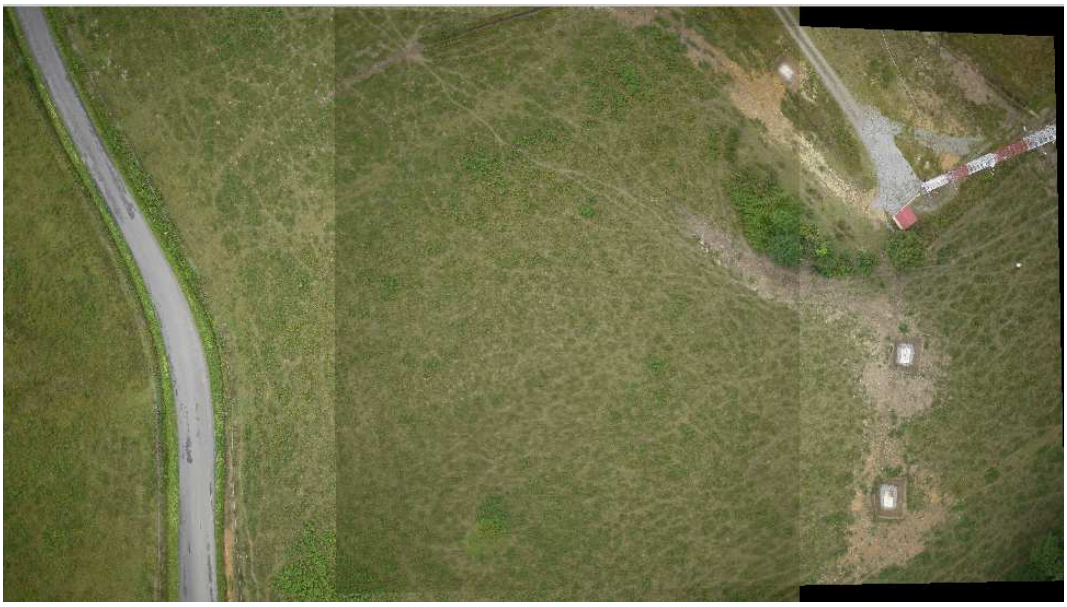
(d) 

Figure 2. Feature matching using RANSAC. (a) and (b) Candidate image pair (c) 3223 inliner matches detected (d) Image mosaic with affine transformation.

3. AUTOMATED PROCESSING WORKFLOW

It is evidenced that SIFT has the capability to provide a high number of distinctive keypoints for image matching in cases where the images contain variability in rotation, scale, illumination and camera perspective. This provides a good basis for its implementation in the AAT workflow for the processing of low altitude UAV acquired imagery. This study proposes a SIFT based workflow, Figure 1, to be implemented to perform the automatic mosaicing of UAV images and at a later stage the full AAT.

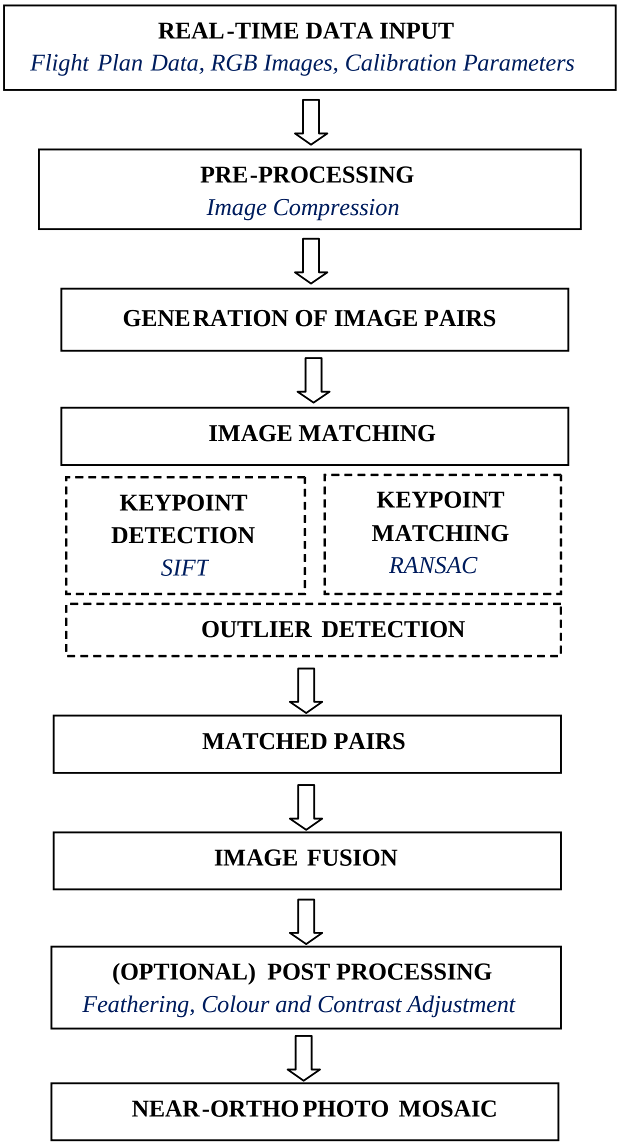


Figure 3. Workflow of proposed automatic image processing method for near-orthophoto mosaic generation from UAV imagery.

The workflow makes use of efficient and robust algorithms to help meet the criteria for near-real time processing. In addition, the GPS flight data is used to create a coarse reconstruction of the aerial strips. This will benefit the image matching process by reducing the search to images with close location proximity. Due to the high overlap present in most UAV images (usually 80%), it is also possible to generate near-orthogonal or minimal distortion images using the central region of the images. This significantly enhances the processing time due to the elimination of orthogonal rectification.

The workflow will be implemented and subsequent experiments will be performed using UAV imagery. The experiments conducted in this study were performed using a sample UAV image dataset obtained from MAVinci (www.mavinci.eu) which was acquired using the company's SIRIUS UAV. The two dataset contains a large number of high resolution images. The scenes are mostly composed of sub-rural and agricultural scenes. It is hoped that further datasets which better represent the clutter and noise characteristic of an urban post disaster scene will be acquired to aid in the conclusion of the success of this method.

Further expansion of the workflow will include the measurement of control points and the bundle adjustment process required to generate numerical products such as DSM or DEM.

4. CONCLUSIONS

A method has been presented for the automatic generation of ortho-photo mosaic from UAV images. SIFT provides a good basis for automatic extraction of highly distinctive features which are useful for matching and robust to changes in scale, rotation, illumination and camera perspective. Efficient algorithms are employed in order to meet the requirements of near-real time processing.

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BIOGRAPHICAL NOTES

Marcus Arthur is a postgraduate research student at the University of the West Indies (UWI), Trinidad and Tobago. He is currently enrolled in the M. Phil Surveying and Land Information program where his interests are in low cost aerial mapping technologies and digital image processing. He holds a Dip. in Building and Civil Engineering and a BSc.(Hons.) in Geomatics.

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