**Feature Extraction and Classification Techniques for UAV Aerial Imaging Applications**

***Abstract - The use of UAVs (Unmanned Aerial Vehicles) to acquire aerial images at high resolutions compared to satellite images have been increasing over the past few years. With higher resolutions, it opened up opportunities to extract more accurate information using image processing techniques for various applications to make better decisions for its respective stakeholders. In this paper, we discuss three techniques in terms of feature extraction and performing classification on UAV aerial images on the following use cases: examining earthquake faults, fishpen monitoring and coconut tree classification.***

I. INTRODUCTION

Unmanned Aerial Vehicles or UAV have been increasingly easier to acquire and deploy for several applications. In September 2013, fixed wing UAVs were used to monitor flooded areas in Colorado by quickly creating a georeferenced map of the area. This information was then used to aid relief efforts to know where resources were to be deployed [1]. In November 2013, Yolanda typhoon devastated the Philippines destroying residential areas, businesses and landscape. UAVs were then used to quickly create a snapshot of the situation in the area by georeferencing stitched images so local government units will be able to take immediate action [2]. Given these examples, UAV applications in the context of aerial imagery for decision making has three main components: deployment of the UAVs (which includes launching the UAV in an area and data acquisition), post processing and information dissemination. This information can then be further analyzed by experts, policy makers and other stakeholders for better decision making. In this paper, we focus on post processing part, specifically using image processing techniques and how it can be used to examine earthquake faults and classification of coconut trees. We first discuss the importance of each problem and present the image processing techniques used for each one.

*A. Examining Earthquake Faults*

In post-disaster inspection from an earthquake, it is necessary to monitor the fault line to determine where this is going in quick and timely manner. The challenge is to isolate the fault line from an aerial image taken by a UAV. The extracted fault line can then be further analyzed by geologists, archeologists or other parties that will be able to take further actions as to the effect of this fault line in the surrounding area. Color transformation and thresholding techniques with K-Means clustering is performed to address this problem.

*B. Coconut Tree Classification*

Coconut trees can be used as carbon sinks to regulate the absorption of carbon produced by the surrounding environment. The challenge is to be able to monitor the status of these trees if they are either planted or fallen. Given that these trees exhibit the same characteristics as its surrounding trees, it is a difficult task to be able to isolate and pinpoint their location in a given aerial image. For this, two approaches are used: conventional templating techniques and superpixel classification.

II. METHODOLOGY

The following table presents a summary of the techniques/approaches used for each use case:

TABLE I

Use Case and Corresponding Image Processing Technique

|  |  |  |
| --- | --- | --- |
| **Use Case** | **Image Processing Technique** | **Software Used** |
| Fault Line Detection | Color space transformation, K-means clustering | Matlab |
| Coconut Tree Classification | Template matching, superpixel classification | Custom C++ program with OpenCV libraries |

*A. Fault Line Detection*

**The following diagram presents a summary of the process involved in fault line detection:

Fig. 1. Block Diagram for Fault Line Detection

Instead of using the RGB color space, we first transform the image to its corresponding HSV color space. This color space consists of hue, saturation and value/intensity. Figure 2 shows the original image with its RGB color space while Figure 3 shows the transformed image with its HSV color space.

[IMAGE]

Fig. 4. Original RGB Image

[IMAGE]

Fig. 3. Transformed HSV Image

To isolate pixels in the image that belong to the fault line, we make use of the saturation channel that has the least contrast value in the transformed image. The saturation channel of the original image can be seen in Figure 3.

Moreover, we applied Gaussian filter to smoothen the image and eliminate salt-and-pepper noise before segmentation. In the stage of image segmentation, the algorithm clusters and divides the image into different regions, which can be considered homogeneous based on a given criterion such as color, contrast, texture etc. To do this, we make use of the K-means clustering algorithm for grouping n pixels. It is an unsupervised classification that finds partitions such that data points with high intra-class similarity and low inter-class similarity. In Figure 4, five clusters are used to group five levels of contrast.

[IMAGE]

Fig. 4. K-Means Clustering Output

*B. Coconut Tree Classification*

For coconut tree classification, we make use of two methods. The first one is a conventional template matching wherein a pre-known image patch containing the object of interest and slide that to each possible position in an image to determine if it contains the object. The second method uses what are called superpixels (groups of pixels) as its basic unit in an image as opposed to single pixels. Each superpixel is then labeled as either one or zero where one contains the object of interest else, zero.

*1) Template Matching*

In order to detect coconut trees, we first extract a sample image patch of a coconut tree. Both the image patch and the image are first converted to a grayscale image from its original RGB image. The image patch is then exhaustively slid over each position in the input image. The following figure shows an illustration of the image patch containing a coconut tree:



Fig. 5. Image Patch Used for Template Matching

If a position in the input image matches the image patch, that position will be labeled as black. Else, it will labeled as white. The output image will then be a binary image to map locations of coconut trees which can then be segmented to produce the final image. The distance metric used to match the image patch from the local patch in the image is done using square difference matching method [4]. The following figures show the result of template matching. From left to right it shows the original image, grayscale, binary then finally the segmented areas.

[IMAGE]

Fig. 6. Template Matching Output

*2) Superpixel Segmentation*

We applied a Superpixel Classification Technique to distinguish cultivated coconut stands from wild forest. This enables, for example, carbon source and sink estimates for carbon trading activities.

Given an aerial image, we group the entire area into homogeneous groups of pixels referred to as “superpixels”. The grouping/clustering method is based on the SLIC (simple linear iterative clustering) algorithm which makes use of the CIELAB colorspace values of an image. The image is first divided into an equal grid of superpixel regions with initial seed centers based on the lowest gradient value. A new center is computed at each iteration and a residual error value is derived by taking the average distance of the current center points generated to its previous center points. To compute for the distance metric of one data point to another, we make use of the following equations:

The first equation is a simple euclidean distance for the *l*, *a*, *b* values of each pixel where *k* is the index of a cluster and *i* is the index of a pixel being examined. The second equation is also a euclidean distance but this time on the *x* and *y* coordinates of the cluster center and a pixel being examined. The third equation is the final distance value where *m* is a constant and *s* is the initial dimensions of a superpixel (if s=20, a superpixel region measures 20x20 pixels at the start of the process).

Once a minimum error threshold is reached, the output would be the same number of superpixel regions with its corresponding pixel members. The iterations are needed to approximate the boundaries of the regions covered by a superpixel [5].

For each superpixel, we extracted a set of feature descriptors which characterizes that superpixel. We used the SIFT descriptors for each superpixel which generates a 128 vector of feature descriptor values. Each vector of feature descriptors can be labelled as some class. In the preliminary experiments, we used a label of 1 for each set of feature descriptors characterizing an area containing coconut trees and a label of 0 otherwise. For classification, we first produced a learned model based on the data using support vector machines. Given an input image and the produced model, we then generated superpixels from the image and labeled them according to the model produced by SVM. The following figures show the original image and the classified image. Superpixels masked with blue are areas containing coconut trees while superpixels masked with orange do not contain coconut trees.



Fig. 6. Original Image with Coconut Trees



Fig. 7. Output of Superpixel Classification

III. RESULTS AND DISCUSSION

For earthquake fault detection, we can see that using the HSV colorspace as opposed to the RGB colorspace allowed emphasis on intensity rather than color information. Because of this, pixels belonging to the actual earthquake fault would have similar characteristics on its saturation intensity levels. To segment the image to isolate the earthquake fault pixels, K-Means was applied against the HSV colorspace. This technique uses an iterative process that groups based on its HSV characteristics. For our test images, using a K value of 5 allowed us to accurately isolate majority of the earthquake fault line.

To segment areas with coconut trees in an image, we explored two techniques. In the first technique, we sampled an image patch containing a coconut tree and exhaustively searched all possible positions that are similar to the template. To segment the trees, we first produced a binary mapping of the input image where black pixels label areas that match with the template provided, else white pixels to label areas that mismatch with the template. Although we achieved good results based on this technique wherein majority of the areas with coconut trees were detected, its main weakness is that it only makes use of one template for comparison causing a lack of diversity for other possible features of the object of interest.

The second technique makes use of superpixel classification wherein we first divide the image into homogeneous regions called superpixels before extracting features from each superpixel. After gathering enough superpixels for both areas containing and not containing coconut trees, we extract SIFT features from them and produce a learned model using support vector machines. Although the output showed that using this approach, we were able to segment most areas containing coconut trees, the process also produces false positives such as areas belonging to the river. This is because the features extracted from each superpixel is merely based on orientation values and not color information. As a result, superpixels in water containing similar orientation values from the trained dataset will be likely to be classified as coconut trees.

IV. CONCLUSION AND RECOMMENDATIONS

In this paper, we’ve presented three image processing techniques that can be applied to aerial images acquired by UAVs. We were able to successfully segment areas of interest such as earthquake faults using k-means on HSV colorspace and detect areas with coconut trees using template matching and superpixel classification. To add more value for the stakeholders that would use this information, a recommended next step would be to overlay and georeference this information on a stitched version of multiple images.

REFERENCSE

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