

SUPERVISED CHANGE DETECTION TOOL FOR DUBAISAT-1 MULTISPECTRAL IMAGES

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Abstract

This paper presents a novel change detection tool for multispectral remote sensing images based on already existed methods which are Algebra change detector algorithm and Support Vector Machine (SVM) classifier. Unlike other change detection commercial tools, this tool not only highlights the areas of change, but also reports and describes the changes that had happened in an image. The description includes the change of class an area had gone through and the change percentage of each class in an image. The tool can detect as small as one-pixel change utilizing up to seven classes to describe it. Moreover, it is able to discard any detected changes that are resulted from shadows or any undesirable color contrast. These features together make the tool a powerful, yet easy and timesaving way to serve analysis purposes.

Keywords: Change Detection, Multispectral Images, Supervised Classification, Algebra Change Detection, Thematic Map

1 INTRODUCTION

Geographical changes that results naturally or from human interference are happening every day in a fast-pace that most of the time our minds cannot comprehend. These changes can be captured by earth observation satellites and analyzed through different types of software. The analysis process and results are very important and can be used for, but not limited to, environmental and geographical studies, and projects management.

To serve this purpose, there are many commercial change detection tools in the market like DeltaCue in ERDAS IMAGINE, Difference Change Detection in ENVI, and Optical Change in PCI Geomatica. The mentioned tools are similar as they all manage preprocessing, multiple change detection algorithms, and change filtering. Yet, they come short in describing the type of changes the study area went through and no form of reporting is provided. Thus, the main objectives of the Supervised Change Detection tool (SCDT), explained in this paper, are not only to detect but analyze the changes in a study area and provide a friendly reporting to the analyst.

SCDT is initially developed and tested for DubaiSat-1 multispectral images. DubaiSat-1 is a remote sensing Earth observation satellite that is owned by Emirates Institution for Advanced Science and Technology (EIAST), United Arab Emirates. It captures images using a pushbroom camera with a 5m resolution for multispectral images and 2.5m for panchromatic images.

2 METHODOLOGY

SCDT is an interactive tool written using Matlab program to automatically detect and highlight the changes between two DubaiSat-1 multispectral images of a specific area, taken at different times. The SCDT is developed to ease the analysts' job in detecting the smallest changes that study areas go through along with its analysis results. The idea of the tool is to classify the images provided by the analyst according to the number of classes that is specified by the analyst himself. Accordingly, the tool will detect and highlight the areas that had changed their class. The images read by the tool are processed through 3 phases before the analysis results are computed. The three phases are: Algebra Change Detection, Supervised Classification, and Change Filtering. Fig.1 illustrates the flow chart of the tool. It should be noted that images read by SCDT are assumed to be co-registered, geometrically corrected, radiometrically corrected, and have similar atmospheric conditions. Further, they are assumed to have the same dimensions and contain 3 visible bands: Red, Green, and Blue. The study area used for this paper is for Palm Jumeirah in 2011 and 2012 as Fig.2 shows.

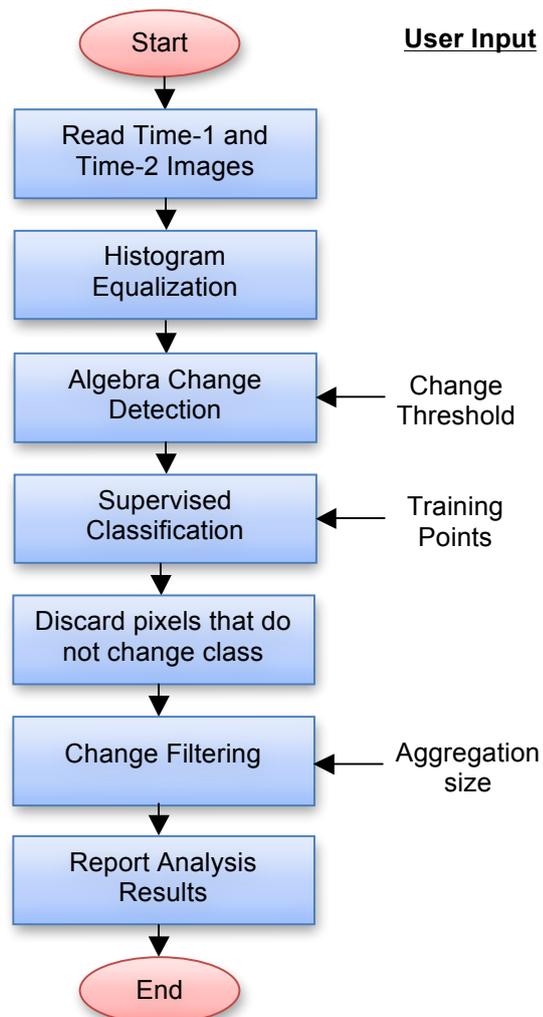


Figure 1: SCDT flow chart



Figure 2: Palm Jumeirah images captured by DS-1 on 27/06/2011 (left) and 02/03/2012 (right)

2.1 Algebra Change Detection

According to [1], Algebra Change Detection (ACD) is an image differencing technique, where each pixel in time-1 image (X_1) is subtracted from its corresponding in time-2 image (X_2) where both X_1 and X_2 are 3-bands images (RGB). The images in the differencing equation are normalized.

$$D = X1 - X2$$

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The output of the magnitude difference (D) is a matrix of the same size of the images containing either zero, positive, or negative values, which varies between [1,-1]. Positive and negative values indicate changed pixels, whereas zero-valued pixels indicate no change. Since this technique is heavily dependent on pixels' digital number (DN), any color contrast difference will result in non-zero-valued pixels. Thus, prior to ACD, the images will be histogram-equalized. Then the analyst will specify a change threshold (Tc) in terms of percentage to differentiate between changed and non-changed pixels. Any pixel in D that exceeds Tc will be marked in a new matrix called (C). Because D has 3 bands, a pixel is defined as change if and only if the three bands met or exceeded the condition of Tc.

$$C_{ij} = \begin{cases} 0, & |D_{ij}| < Tc \\ 1, & |D_{ij}| \geq Tc \end{cases} \quad 2$$

As Tc increases, the number of detected changes decreases dramatically. This can be shown for Palm Jumeirah Image in Table-1. At Tc=20%, the detected changes included the actual changes in addition to shadows and contrast changes, which do not necessarily reflect any actual changes. On the other hand, at 50% threshold, the detected changes were very few because a very high contrast change is required to detect a change (i.e. 128 DN change) and this can be considered a very strict threshold and not practical for this application. It is good to note that Tc is solely dependent on the analyst perspective, the study image, and the application purpose.

Table 1: Impact of Tc on ACD results (Changes colored in red)

Tc	Result	Tc	Result
20%		40%	
30%		50%	

2.2 Supervised Classification

Although ACD method detects the changes that happened in an area, it fails to tell the type of change that had happened. Further, it falsely marks unchanged pixels as "change" because of the shadow effect. To compensate for that, the SCDT classifies *only* the detected changed pixel in both images

and compare their classes. If the detected changed pixel happened to not change classes, the pixel is discarded and is treated as “no change”.

In theory, there are two general types of classification: supervised and unsupervised. In SCDT, supervised classification is used to take advantage of the prior-knowledge the analyst has of the study area. The use of supervised classification limits the use of the tool to study areas that the analyst can identify its features. In supervised classification, the analyst select training points for each pre-defined class, and then the training points are used to classify pixels. Many types of classifiers are introduced in [2] like maximum likelihood, minimum distance, parallelepiped, and support vector machine (SVM). Because SVM can capture the complex relationships between the training points, it is chosen to be used for SCDT. On the down side, it is computationally intensive, and the classification time varies depending on the size of data to be classified. Since the accuracy of the classification results are more important than time in SCDT case, this downfall is neglected for the time-being. The SVM code in the SCDT is taken from [3].

The tool has 7 pre-defined classes which are: undeveloped areas, greenery, roads and paved areas, urban, water, others1, and others2 (which are user-customized classes). These seven classes are chosen depending on the geographic nature of United Arab Emirates. The analyst is allowed to utilize some or all the classes for classification. It is recommended that the analyst train classes others1 and others2 for shadows or any undesirable color contrasts. This will give the analyst the option to include or discard the pixels related to these classes and treat them as “no change”. After the pixels marked in matrix C (mentioned in equation 2) are classified in time-1 and time-2 images, the tool compares time-1 and time-2 classes. When the tool notices no change in class for a pixel, it discards it from C matrix and treats it as “no change”. Fig.3 shows the classification of detected changes for Palm Jumeirah study area.

■ Water ■ Undeveloped Area ■ Urban ■ Greenery ■ Roads & Paved Areas □ Unclassified



Figure 3: Palm Jumeirah classified images on 27/06/2011 (left) and 02/03/2012 (right)

2.3 Change Filtering

The output of the classification phase is an image that is marked with changed pixels that exceeded the T_c threshold, and that experienced a change in classes in the supervised classification. The analyst is given the option to filter the changes by defining the aggregation size in pixels. The aggregation size is a threshold that defines the minimum number of changed pixels that are connected together. In other words, the aggregation size is the minimum size of changed areas in the study image. If the analyst defined an aggregation size of 50pixels, SCDT will label the connected pixels with a single label. Then the number of pixels under each label will be computed and compared to the aggregation size. If the number was less than 50pixels, all the pixels under the label will be discarded and treated as no change, otherwise, it will be kept as it is. There is no optimum number for the aggregation size. It is dependent on the type and size of changes the analyst wants to detect in the study image.

3 PRELIMINARY ANALYSIS RESULTS

SCDT outputs 3 main results: time-1 and time-2 images with the changes highlighted with a box, change description, and change percentage for each class. For the first output, the analyst has the option to display time-1 and time-2 images with the changes including or excluding the shadows. This option is only available if the analyst had used others1 and others2 classes for shadows. Fig.4 and Fig.5 show the difference between both results.



Figure 4: Changes *including* the ones resulted from shadows in Time-1 (left) and Time-2 (right) images



Figure 5: Changes *excluding* the ones resulted from shadows in Time-1 (left) and Time-2 (right) images

As for the change description, SCDT displays a table to the analyst that indicates the change in classes each area had gone through. Table 2 shows the corresponding change description for Palm Jumeirah image. Each number in the table corresponds to a specific numbered box in Fig.5.

Table 2: Change Description (Excluding Shadows)

	Change From	Change To
1	Water	Undeveloped Area
2	Vegetation	Undeveloped Area
3	Water	Undeveloped Area
4	Undeveloped Area	Vegetation
5	Undeveloped Area	Vegetation
6	Road	Undeveloped Area
7	Water	Undeveloped Area
8	Undeveloped Area	Road

Last displayed is the change percentage for each class in the study area to provide a mathematical significance to the analyst. The percentages can be positive or negative where the first indicates a class expansion and the second indicates a class reduction.

Table 3: Percentage of Change for each class

Class Name	Change Percentage
Undeveloped Area	0.0756
Water	-0.0754
Urban	-1.0142e-04
Vegetation	0.0045
Roads	-0.0046
Unclassified	0

From Table 3, the analyst can tell easily that water class was reduced in time-2 image compared to time-1 image, and this figure is easily supported by Table 2 results where changes no.1, 3 and 7 proves that these water areas had been buried by sand to form undeveloped areas. The three outputs works well together to explain the changes using visual and percentage proofs.

4 CONCLUSIONS AND FUTURE WORK

SCDT is a supervised change detection tool that aims to ease the analyst's job when analyzing change detection results of a study area. It utilizes ACD technique, supervised classification, and change filtering processes to come up with a friendly reporting of the occurred changes. The analysis report provides a visual proof of the changes highlighted with a box, a change description, and a change percentage of each class used for classification. The accuracy of SCDT results is solely dependent on the analysts' inputs: the change threshold in ACD, the training points in classification, and aggregation size in change filtering.

As for the future work, a comparison between SCDT and the famous change detection tools in ENVI, ERDAS IMAGINE, and PCI Geomatica software will be conducted. A measure of accuracy will be used to evaluate the tools' performances.

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Hessa Almatroushi has joined Emirates Institution for Advanced Science and Technology in April 2013 as an Associate Image Processing Engineer. She has a bachelor degree in Electrical Engineering from American University of Sharjah (UAE) and is pursuing master degree in Engineering System Management from the same university.

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