On-Board Automatic Change Detection System for Disaster Monitoring

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Abstract – This paper presents a new approach to disaster monitoring using an automatic change detection system on board small satellites, which features image tiling and fuzzy inference. Unlike other on-board change detection systems for satellites, the proposed system performs change detection on an image tile level rather than on a pixel-by-pixel basis. This image tiling approach allows for more robust change detection performance in the presence of misregistration errors. An important block in the automatic change detection system is the fuzzy inference engine, which generates control signals that trigger different on-board tasks such as image compression, issuing of warning alerts, transmission and rescheduling. The proposed scheme uses not only spectral information as the input data, but also cloud cover information to improve the change detection results. Experimental results on accuracy of change detection and flood detection using satellite images are presented.

1 Introduction

Man-made and natural disasters can cause devastation resulting in casualties, loss of infrastructure and livestock on an enormous scale. For example, the earthquake and Tsunami disaster that struck south-east Asia in December 2004 (Lay *et al.* 2005) resulted in the death of 160,000 people and 5 million more people were displaced. The total cost of damage is estimated to be around USD 2 billion (Brakenridge 2005). In the following year, the hurricane Katrina resulted in the flooding of New Orleans, USA (Travis 2005, National Oceanic and Atmospheric Administration 2007), which caused damage of USD 60 billion (Brakenridge 2006). As natural disasters can cause great loss of life and infrastructure it is very important to have in place systems that can effectively predict, detect and monitor such events facilitating rapid response and rescue efforts.

Earth Observation (EO) satellites flying in low Earth orbit (LEO) have been used as a tool to monitor disasters by providing satellite imagery. These satellites supply valuable data for assessment of the damaged areas (Borrero 2005, Chen *et al.* 2005, Miura *et al.* 2006). However, they do not have on-board capabilities to carry out real-time processing and decision making operations, required for quick and rapid responses to disasters, such as mapping, prediction and issuing of warning alerts. Traditionally EO satellites follow a “store-and-forward” scheme, in which the captured images are stored on board before being transmitted to the ground station. This mechanism causes delay and is not suitable for rapid response, as the images are

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delivered for subsequent processing only when the satellite arrives at the nearest ground station. Due to the lack of global network of ground stations, the transmission of the images could be delayed as LEO satellites would pass several orbits before reaching the required ground station.

Intelligent processing capabilities on board EO satellites could speed up the response time significantly by extracting information from the images before they are transmitted to ground. For example, selective image compression could be performed on board the satellite so that only relevant images are transmitted to ground. The captured images could also be processed on board to check for changes in the monitored areas. In fact, the ability to detect temporal changes in images is one of the most important functions in intelligent image processing systems for hazard and disaster monitoring applications. This capability could ensure a quick response that would greatly benefit the monitoring of disasters such as floods, earthquakes, oil-spills, etc..

An automatic change detection system for small satellites is being developed at the Surrey Space Centre, which is targeted at on-board flood monitoring (Yuhaniz *et al.* 2007). This paper presents a new approach to change detection, which is based on image tiling and fuzzy inference. Unlike other change detection systems, the proposed system performs change detection on a tile-by-tile rather than on a pixel-by-pixel basis. The paper is organised as follows. Section 2 discusses background issues and related work. Section 3 describes the proposed on-board automatic change detection system. Section 4 discusses experimental results. Section 5 concludes this paper.

2 Background

Small EO satellites are a recently developed category of EO satellites weighing less than 500 kg whose main function is to observe the Earth. The small satellite concept has been pioneered by Surrey Satellite Technology Limited (SSTL). Unlike the large EO satellites that are bigger and take longer time to build, small EO satellites offer a cheaper and faster approach to satellite development. Furthermore, due to their lower design and manufacturing costs, small satellites offer a viable platform for EO constellations in LEO, which provide more frequent observation (Stephens 2007). For example, the Disaster Monitoring Constellation (DMC) developed by SSTL, which comprises five micro-satellites, provides daily imaging of any point on the globe. The standard DMC platform carries 32 m multispectral imagers with a very wide swath of 600 x 600 km. The DMC satellites have captured images of all disaster areas since 2003 including the 2004 Tsunami in South East Asia. However, image processing on board small satellites is a very challenging task due to limited computing resources.

There are two main image processing functions on board an EO satellite: image compression and autonomous image analysis and selection. The purpose of the image analysis and selection function is to analyse, detect and classify the image according to certain characteristics. Automated remotely sensed change detection analysis is a particularly useful feature for disaster monitoring on board satellites. A general process of change detection takes as inputs two images: a reference image and a sensed image, which are captured at different times. The two images need to be pre-processed so that they are in the same space representation. Pre-processing is an important component, which involves the operation of registration. The output of the change detection is a change image, which contains change and no-change information. The change image is then been analysed to extract changes relevant to the user. Main problems in change detection systems for remote sensing are finding

the threshold between change and no-change areas, sensitivity to registration noise, and cloud cover in case of optical images.

The need for disaster monitoring from space and the emergence of small EO satellite platforms has initiated a number of research projects targeted at advanced on-board image processing. This has enabled the launch of satellites with sophisticated imaging payloads. On-board image compression and cloud detection are the earliest on-board image processing units that have been developed and launched on small EO satellites as demonstrated by UoSat-5 (Montpetit *et al.* 2003). Fire detection based on image processing has also been demonstrated on board the BIRD satellite (Haller *et al.* 2002).

Change detection is relatively less developed than the other on-board image processing functions due to the complexity of the change detection process. Furthermore, high accuracy of registration is needed to ensure the accuracy of the change detection analysis due to change detection methods being sensitive to misregistration errors. The only known change detection system on board a satellite is the NASA Earth-Observation 1 (EO-1) spacecraft, which belongs to the category of large satellites. EO-1 performs change detection as part of its on-board flood detection algorithm (Ip *et al.* 2006) and cryospheric detection algorithms (Dogget *et al.* 2006). The algorithms are developed under the Jet Propulsion Laboratory's (JPL) Autonomous Sciencecraft Experiment. The project includes the development of on-board science algorithms such as image classification, compression, and change detection. The change detection process is performed by comparing the total number of detected feature pixels with uploaded threshold values to trigger follow-up observations. A different approach to on-board change detection is proposed in (Spigai and Oller 2002), where the change detection is used together with image compression and neural-network based classification. When changes are detected in an image tile, neural-network classification is performed to identify the features in the changed image tile and the rest of the unchanged areas are then compressed. However, this work does not discuss issues related to the implementation of the change detection approach in a satellite platform.

A few authors have analysed the effect of image misregistration on the accuracy of remotely sensed change detection. Dai and Khorram (1998) report that change detection accuracy drops dramatically within the first pixel of misregistration. Also, Townshend *et al.* (1992) perform an evaluation of the effect of misregistration errors on moderate resolution satellite imagery, concluding that highly accurate registration is needed in order to achieve a reliable change detection system. This is confirmed by the evaluation of the accuracy and computing performance of several image registration and change detection methods on different computing platforms (Yuhaniz *et al.* 2005).

The review of the literature has shown that there is a trend towards increasing computing power and resources on board satellites, which will enable the implementation of advanced image processing functions, such as change detection, in future remote sensing satellite payloads (Vladimirova *et al.* 2006).

3 Change Detection Processing Model

Change detection analysis is not a straightforward task, which is different from the other image processing tasks that only process a single image, such as image compression and image encryption. It is a multi-temporal analysis, where two or more co-registered images are compared to establish the changes. The quality of the image

registration is very critical as the change detection process is sensitive to registration errors. In this section a new change detection processing model is proposed that uses information from a group of pixels rather than a single pixel to overcome this problem.

The traditional change detection process works on a pixel-by-pixel basis. Each corresponding pair of pixels in the two input images is compared resulting in a value that represents the degree of change. A threshold then determines if the pixel is considered changed or not changed. The output of the change detection analysis is a change image that contains changed and unchanged pixels. The threshold value selection is a critical task in change detection analysis as a wrong threshold would lead to a wrong result. The threshold is always being set manually from trials or statistically from the mean of the change image since there are no sharp boundaries between changed and unchanged areas.

In the proposed model both images are automatically split into tiles of a pre-defined size. Change features are detected by comparing every tile to its matching reference tile which increases the efficiency of change detection in the presence of misregistration in the images. To overcome the threshold selection problem, a fuzzy inference engine block has been introduced in the system (Yuhaniz *et al.* 2007). Decision is then made based on the comparison results using an inference engine. In this change detection processing method, the output of the system is a collection of change detected image tiles.

3.1 Image Tiling and Comparison

Change detection methods could broadly be divided into two types: pre-classification and post-classification (Dai and Khorram 1998). Pre-classification methods identify changes by comparing the reference and sensed images pixel by pixel and then, a threshold is used to separate the changed and not changed pixels. Post-classification methods perform feature classification on the two images, which is followed by comparison of the classified images pixel by pixel to identify changed features.

Different from the traditional pixel-to-pixel change detection process, this work proposes a change detection model by tiling the reference and sensed images and detecting changes on a tile-by-tile basis. Let $\mathbf{X}_s$ be the sensed image from the satellite imager and $\mathbf{X}_r$ is the reference image. The approach is to split the images into a set of N image tiles $\mathbf{X}_{s_i}$, $i = 1, \dots, N$ and $\mathbf{X}_{r_i}$, $i = 1, \dots, N$, of user-defined size. Each set of image tiles for the sensed and reference images are compared to find their degree of change. The output of this step is a set of image tiles that have a degree of change above the threshold, represented by the set $\mathbf{X}_D = \{\mathbf{X}_{D_i}, i = 1, \dots, N\}$.

The set of degree of change values, $\mathbf{X}_D$, becomes the input to the fuzzy inference engine described in section 3.2, which determines if the image tile is considered changed or not. Three strategies to calculate the degree of change set $\mathbf{X}_D$, are defined, which are explained below:

Option 1: *Percentage of changed pixels in each pair of image tiles.* $\mathbf{X}_{D_i}$ is calculated by determining the percentage of the total number of changed pixels over the total number of pixels in each tile:

$$\mathbf{X}_{D_i} = a / n \quad (1)$$

where n is the total number of pixels in the image tile, a is the total number of pixels in each image tile that have satisfied the following condition:

$$|x_s - x_r| > T \quad (2)$$

where x_s and x_r are the pixel values for images $\mathbf{X}_s$ and $\mathbf{X}_R$ respectively; T is the threshold that separates changed and not changed pixels.

Option 2: *Correlation coefficient for each pair of image tiles.* $\mathbf{X}_{D_i}$ is determined by calculating the correlation coefficient of the pair of image tiles. The correlation coefficient measures the similarity between the pixels in the sensed image tile and its corresponding reference image tile. The correlation coefficient for image tile i is calculated as:

$$\mathbf{X}_{D_i} = \frac{\sum_{k=1}^n (\mathbf{X}_{R_{ik}} - \bar{\mathbf{X}}_{R_i})(\mathbf{X}_{S_{ik}} - \bar{\mathbf{X}}_{S_i})}{\sqrt{\sum_{k=1}^n (\mathbf{X}_{R_{ik}} - \bar{\mathbf{X}}_{R_i})^2 (\mathbf{X}_{S_{ik}} - \bar{\mathbf{X}}_{S_i})^2}} \quad (3)$$

Option 3: *Difference of means for each pair of image tiles.* $\mathbf{X}_{D_i}$ is determined by calculating the mean for each tile i of images $\mathbf{X}_s$ and $\mathbf{X}_R$:

$$\mathbf{X}_{D_i} = \left| \sum_{k=1}^n \frac{\mathbf{X}_{R_{ik}}}{n} - \sum_{k=1}^n \frac{\mathbf{X}_{S_{ik}}}{n} \right| \quad (4)$$

3.2 Fuzzy Inference Engine

A large and growing body of literature has investigated the use of fuzzy logic in connection with the classical change detection analysis. Most of the existing methods for automatic change detection use crisp models for the selection of the threshold value. In such models, the boundary between changed and unchanged areas is determined without taking into account the uncertainty caused by the overlapping between those areas. Fuzzy logic has been used to solve the change detection threshold problem by mapping the image histogram to its fuzzy membership function (Metternicht 1999), or by mapping the log-ratio image histogram to its fuzzy membership function (Carincotte *et al.* 2006). The use of fuzzy logic in post-classification comparison change detection techniques has been developed by Deer and Eklund (2002). In their work, fuzzy classifiers are used instead of traditional hard classifiers during the feature classification steps before detecting changes.

Inference engines are another application of fuzzy sets and logic. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic (Kong and Kosko 1992). The mapping then provides a basis from which decisions can be made, or patterns discerned. It has been used in many applications including computer vision, data classification and automatic control. A fuzzy inference system has three components: fuzzy membership functions, fuzzy operator and if-then rules. A simple example of using a fuzzy inference engine for image classification can be found in (Nedeljkovic 2004).

Although the use of fuzzy logic in change detection analysis is an active research area, there are very few literature sources on using fuzzy inference in a remote sensing change detection system. De Souza *et al.* (2002) propose the use of a fuzzy inference system to detect land-cover changes. The input to the system is a degree of change for each pair of pixels that represents the absolute value of the differences between two images of the same band. This method uses a pixel-to-pixel comparison scheme to create the change image, which is prone to the classic change detection problems of sensitivity to misregistration errors.

In this research work, a fuzzy inference processing block is introduced, called fuzzy inference engine (Yuhaniz *et al.* 2007). The block-diagram of the fuzzy inference engine is shown in Figure 1. The fuzzy inference engine receives two input variables and generates one output variable. The two input variables represent: 1) the degree of change value from the change detection processing block and 2) the percentage of cloud cover from the cloud cover processing block. The output variable denotes the control alerts, which will be sent to other sub-systems for subsequent actions to be triggered.

The advantage of this approach is that there is no direct pixel-to-pixel comparison, which makes it to be more robust to misregistration noise. Moreover, this approach allows for easy future modification if additional parameters are needed to be included in the inference engine, for example, current weather information from terrestrial weather databases, etc.. The outputs of the inference engine are warning alerts and control signals to other on-board sub-systems to perform image compression, schedule the next imaging task or transmit the changed image tile, etc..

The fuzzy inference engine in Figure 1 uses the Mamdani's fuzzy model, which is the most frequently employed fuzzy methodology. Ebrahim Mamdani (1975) proposed the model as an attempt to control a steam engine and boiler combination. The input and output of the Mamdani's fuzzy model are represented in linguistic form so that they can be understood by a human. Thus, the variables for the fuzzy inference engine can be easily designed and adapted from expert decision-making experience.

Figure 2 shows the graph of the fuzzy membership function for the input variable X_D , or "degree-of-change". The range of this variable is divided into three fuzzy sets called "low-change", "medium-change" and "high-change". Figure 3 shows the membership function for the input variable, "perc-cloud-pixel", which represents the percentage of clouded pixels in each image tile. Similar to the "degree-of-change" variable, this variable is divided into three fuzzy sets called "low-cloud", "medium-cloud" and "high-cloud". Figure 4 shows the fuzzy membership function of the output variable "control-signal", which generates control signals for the subsequent on-board sub-systems. A "no-alert", "medium-strength-alert" or "high-strength-signal" value determines the next relevant processing task.

Nine rules are created for the fuzzy inference engine, which is realised by the fuzzy associative memory shown in Table 1. The rules indicate the type of outputs that are generated when two input variables, "degree-of-change" and "perc-cloud-pixel" are applied to the inference engine. For example, when the input variable of "degree-of-change" has a "low-change" value, and the input variable "perc-cloud-pixel" has a "high-cloud" value, then the output that is generated is "medium-strength-alert".

3.3 System Architecture

This section outlines the system architecture of the proposed automatic change detection system for a small satellite shown in Figure 5. The system comprises a database, which is implemented in the form of a hard disc drive, to store reference images and newly generated images.

The rectangle boxes in Figure 5 denote the processing blocks of the system: image tiling, image registration, cloud detection, change detection, fuzzy inference engine and database update. The cylinder block denotes an on-board database to store the results of the processing. The parallelogram blocks denote the data that flows between the processing blocks: 1) the sensed image, which comes from the on-board imager, 2) the reference image, retrieved from the on-board database, which is compared with the sensed image, and 3) the processed image tile from the change detection processing block that is used as the input to the fuzzy inference engine block.

The system operation starts when receiving an image from the imager. Global positioning system (GPS) data are used to "stamp" the images with the geo-location at the time of capture, providing additional information for the subsequent tasks of image co-registration and identification of the reference image in the database. After receiving the sensed image, the image is tiled according to a pre-determined size. Next, each of the sensed image tiles are co-registered to the reference image using the ground control points available on both of the images.

Cloud detection is performed with the Automatic Cloud Cover Assessment (ACCA) algorithm (El-Araby 2005) which has been used in processing of Landsat images. Next, the registered tile images are compared using one of the degree of change calculation options described in section 3.1. The output of the change detection and image comparison processing block then becomes the input to the fuzzy inference engine that generates control alerts of various strength to activate different on-board processing tasks, such as, image compression, image scheduling and high priority transmission.

4 Experimental Results

This section presents experimental results on the accuracy assessment of the change detection system with synthetic and satellite images.

4.1 Testing with Synthetic Images

Three image data sets with synthetic changes are used to test the accuracy performance of the proposed change detection model as specified in Table 2. The reference test image for all sets is the aerial image of the Pentagon in Figure 6 (Signal and Image Processing Institute 2005). Two different types of noise are tested: misregistration errors and salt and pepper noise. Test image set #1 consists of the reference image and a "sensed" image generated by introducing synthetic changes in the original Pentagon image. Image data sets #2 and #3 contain "sensed" images which in addition to the changes in data set #1 include artificially introduced 1-pixel shift misalignment and salt and pepper noise, respectively.

One way of measuring the accuracy of feature detection is based on the confusion error matrix in Table 3. Omission error (or producer's accuracy) measures the error caused by detecting changed areas as non-changed, which results into a missed change alert. Commission error (or user's accuracy) measures the error caused by detecting unchanged areas as changed, which will generate a false alarm. Overall

accuracy measures the accuracy of the change detection method without taking into account the source of error (omission or commission).

The Pentagon images (512 x 512 pixels) are tiled into 1024 tiles of size 16 x 16 pixels each. As proposed and discussed in section 3.1, three options are used to calculate the degree of change in the change detection processing block. Option 1 is based on using the percentage of changed pixels, Option 2 uses a correlation coefficient and Option 3 uses the difference of means. The accuracy is measured by comparing the results from the fuzzy inference engine with ground truth images using the confusion error matrix in Table 3. However, as there are three categories of results from the fuzzy inference engine (high-strength-alert, medium-strength, no alert), and two categories of ground truth (changed and unchanged), the results are adjusted accordingly.

The results of the accuracy assessment of the proposed change detection model for the image data sets specified in Table 2 are presented in Tables 4 and 5. Table 5 also contains accuracy results for the three image data sets when the change detection is carried out using the image differencing method for comparison purposes. This method subtracts each pixel value in one image from the corresponding pixel value in the second image to get the change image. Data with non-zero values mean change area, and zero or near to zero values are no change areas in the resultant change image.

Table 4 shows that the fuzzy inference engine works well on image data set #1 with all three degree of change calculation options as most of the unchanged image tiles generate a no-alert signal. This is expected as this data set is the simplest case of a change detection problem, where there is no misalignment and no noise exists in the test image. The accuracy results on image data set #1 in Table 5 show that Option 3 is the best method among the tested options with overall accuracy of 97% and a low omission error of 2.5%.

The results for image data set #2 present different outcomes for the three processing options of the degree of change. It can clearly be seen from Table 4 that Option 1 which involves pixel-to-pixel comparison has failed to perform, producing an overall accuracy of 5.86% (Table 5). Option 2 and Option 3 perform better than Option 1, and also better than the image differencing method which shows very bad performance at the overall accuracy of 2.13%. This is to be expected as this data set simulates misregistration errors. The pixel-by-pixel image differencing method also performs very badly with 2.13% overall accuracy for the same reasons.

Image data set #3 gives rise to better results than image data set #2 with all three degree of change methods producing high overall accuracy results of more than 95% as seen from Table 5. This shows that the salt and pepper noise does not affect the change detection process as much as the misregistration noise does.

4.2 Testing with Satellite Images

The proposed change detection scheme is also tested on multispectral satellite images for the purpose of flood detection. Three spectral bands are used – Near Infrared (NIR), Green and Red. Three satellite image data sets #4, #5 and #6 are shown in Figures 7, 8 and 9, respectively. The images represent different parts of the coastal areas of Banda Aceh, north Sumatra, Indonesia, which were very badly hit by Tsunami on 26 December 2004. The before-flooding reference images are from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery on 15 August 2001. The after-flooding images are taken by the SSTL UK-DMC satellite on 4 January 2005 in

the aftermath of the Tsunami disaster. The test images in Figures 7, 8 and 9 are represented in false colour, where the vegetation appears in red. They consist of 500 x 500 pixels and are tiled into 625 tiles of size 20 x 20 pixels. The area covered by each of the images is 16 x 16 km².

As flood detection is a special case of change detection (finding changes of non-water to water areas), the flood detection process is performed in the change detection processing block (Figure 5). The proposed automatic change detection system, presented in section 3, uses tile information instead of single pixel information for decision making. In the flood monitoring process this concept is modified to detect flood. A detailed block-diagram for the flood detection processing block is presented in the Figure 10. The inputs to the flood detection processing block are the reference and the sensed image tiles that have been registered in the image registration processing block. Based on performance evaluation of a number of flood detection methods it has been found that NIR/Red differencing gives the best results (Yuhaniz *et al.* 2007). In this method image pixels are determined as water if the ratio of Near Infrared and Red bands is lower than a threshold denoted by T_0 . The value of the threshold T_0 is defined by the histogram of NIR/Red, which is in bimodal distribution. T_0 is located between the two peaks of the histogram, where one peak is for water and the other peak is for non-water areas (Sheng *et al.* 2001).

The change detection process in the flood detection block in Figure 10 is performed on the ratio image of the NIR and Red bands using the proposed change detection scheme as described in section 3 whereby the process generates a degree of change value for each pair of NIR/Red image tiles. The degree of change becomes the input to the fuzzy inference engine that decides if the tile is considered flooded or not. If T_0 is used to threshold the pixels, some ambiguous pixels would be wrongly classified as water or non-water. However, using fuzzy logic, not only the water and non-water pixels but ambiguous pixels can also be considered in the flood detection process. The pixel values can be either water, ambiguous or non-water. The membership function will define how close the ambiguous pixels are to either water or non-water pixels.

Ground truth images are generated manually by visual inspection for all the three satellite data sets as shown in Figures 11(a), 12(a) and 13(a). The white colour on the ground truth images represents the flooded areas and the black colour - the not flooded. Figures 11(b), 12(b) and 13(b) show the results of the flood detection process, with the black areas denoting the unchanged areas. The flood monitoring accuracy results are presented in Table 6. The assessment of the accuracy results is summarised in Table 7, which includes also data based on a pixel-by-pixel method for comparison purposes.

A total of 70 flooded image tiles generate high and medium strength alerts for image data set #4 as seen in Figure 7. This result shows that the proposed system successfully generates flood alerts for most of the flooded areas, however, a few false alarms (commission errors) are also generated (Table 7). The system achieves overall accuracy of 93.76%, with a commission error of 16.67% and a small omission error of 4.62%. While the system generates high or medium strength alerts for 50 of the flooded image tiles of test image set #5, it produces a commission error of 40.63% as shown in Table 7. Nevertheless, the overall accuracy of the system on this test data set is 92.96%, with an omission error of 5.23%. It can be seen from the results for the image data set #6 that the system successfully detects most of the flooded and non-flooded areas with 92.48% of overall accuracy, lower commission error of 31.58% and omission error of 5.11%.

It can be seen from Table 7 that the proposed method performs well generating better results than the pixel-by-pixel method for image data sets #4 and #5 and achieving comparable results with respect to image data set #6.

4.3 Discussion

The test results presented above confirm that the proposed approach based on tile-by-tile change detection and fuzzy inference is more robust against registration noise. The system achieves good accuracy for flood detection too.

The fuzzy inference engine shows to be an effective tool and a suitable replacement to pixel-by-pixel change detection methods, which are based on a manually detected crisp threshold values. Careful tuning of the fuzzy rules has the potential to improve the change detection accuracy significantly.

A novel solution to flood detection for small satellites is proposed in (Yuhaniz *et al.* 2007) combining GPS reflectometry data and optical images. The ability of GPS reflections to penetrate cloud cover will act as a valuable complement and backup for the flood maps produced from the optical images. The fuzzy inference engine could easily be modified to take input from GPS signals as well as other complementary data sources.

Because the tile-by-tile approach works over a larger area the change metrics are “averaged” and some information could be lost if the image tile size is too big. However as the image tile decreases in size, the effects of misregistration would increase. Smaller image tile sizes increase the processing time too. Experimentation with different tile sizes for various UK-DMC multispectral images has shown that the execution time increases dramatically if the tile size is reduced below the size of 50 x 50 pixels. Therefore, the proposed approach to change detection using image tiles is best suited to disaster monitoring applications like flooding where large contiguous areas are subject to change.

5 Conclusions

An automatic change detection system for disaster monitoring on board small Earth observation satellites is proposed which is based on a simple change detection scheme with novel features such as tile level processing and the use of a fuzzy inference engine to assist in the decision making process.

A new change detection model using image tiling is introduced which enables change detection to be effective even when misregistration errors exist in the images. Different from the traditional pixel-to-pixel change detection process, this approach compares reference and sensed image tiles to generate a degree of change value. Three methods for the calculation of the degree of change value are defined and evaluated. It is verified experimentally that the scheme is more robust to errors caused by misregistration than traditional pixel-by-pixel methods.

The use of cloud cover information in addition to spectral images as input data, improves the change detection results. The fuzzy inference engine could be easily modified to allow for addition of new parameters in future system upgrades. For example, GPS reflectometry signals that penetrate clouds and weather information from terrestrial databases could be incorporated to improve the accuracy of the flood monitoring process.

As the proposed change detection scheme is based on a tile-by-tile processing method the selection of the right size of the image tile is an important issue, which requires further investigation. In order for the system to be suitable for on-board use, a

faster hardware implementation needs to be realised to reduce the lengthy execution time for certain image sizes.

Future work will also address aspects related to mitigation of radiation effects and low-power consumption, as well as application of the proposed change detection scheme to other types of satellite imagery, such as hyperspectral and radar images.

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Figure 1. Block diagram of the fuzzy inference engine block of the change-detection system

Figure 2. The membership function for the input variable “degree-of-change”

Figure 3. The membership function for the input variable “perc-cloud-pixel”

Figure 4. The membership function for the output variable “control-signal”

Figure 5. Block diagram of the proposed automatic change detection system for use on board small satellites

Figure 6. Pentagon reference image.

(a)

(b)

Figure 7. Image data set 4. (a) Before-flooding image (courtesy of USGS) (b) After-flooding image (courtesy of SSTL).

(a)

(b)

Figure 8. Image data set 5. (a) Before-flooding image (courtesy of USGS) (b) After-flooding image (courtesy of SSTL).

Figure 9. Image data set 6. (a) Before-flooding image (courtesy of USGS) (b) After-flooding image (courtesy of SSTL).

Figure 10. Block-diagram of the flood detection processing block

Figure 11. (a) Ground truth image for test image set 4. (b) The result of the flood monitoring system for image set 4.

(a)

(b)

Figure 12. (a) Ground truth image for test image set 5. (b) The result of the flood monitoring system for image set 5.

(a)

(b)

Figure 13. (a) Ground truth image for test image set 6. (b) The result of the flood monitoring system for image set 6.

Table 1. Fuzzy inference engine rules

	High cloud	Medium cloud	Low cloud
Low change	Medium-strength alert	Medium-strength alert	No alert
Medium change	Medium-strength alert	Medium-strength alert	High-strength alert
High change	High-strength alert	High-strength alert	High-strength alert

Table 2. Image data sets with synthetic changes for testing of the proposed change detection method

Data Set No.	Sensed Image	Description of Changes
1	Pentagon image with changes	Synthetic changes are introduced by using black boxes
2	Pentagon image with changes and misalignment	Synthetic changes are introduced and the image shifted by 1 pixel in both x and y directions
3	Pentagon image with changes and salt and pepper noise	Synthetic changes and salt and pepper noise are introduced

Table 3. Confusion error matrix

Ground Truth Detection Results	Changed Area	Unchanged Area
Changed Area	Correct Detection	False Positive (Commission Error)
Unchanged Area	False Negative (Omission Error)	Correct Detection

Table 4. Confusion matrix for the three synthetic image data sets with fuzzy inference and three different types of degree of change

Degree of Change Method	Alert Strength	Ground Truth					
		Changed			Unchanged		
		Data Set #1	Data Set #2	Data Set #3	Data Set #1	Data Set #2	Data Set #3
Option 1	High	0	45	0	0	915	0
	Medium	6	2	6	0	50	0
	No	41	0	41	977	12	977
Option 2	High	4	8	5	0	24	6
	Medium	6	14	7	0	196	9
	No	37	25	35	977	757	962
Option 3	High	16	18	17	0	33	0
	Medium	7	6	7	0	100	0
	No	24	23	23	977	844	977

Table 5. Accuracy assessment for the synthetic image data sets with three different types of degree of change

Degree of Change Method	Commission Error (%)			Omission Error (%)			Overall Accuracy (%)		
	Data Set #1	Data Set #2	Data Set #3	Data Set #1	Data Set #2	Data Set #3	Data Set #1	Data Set #2	Data Set #3
Option 1	0	95.35	0	4.12	0	4.12	95.90	5.86	95.90
Option 2	0	89.32	47.83	3.84	3.06	3.50	96.19	79.60	95.51
Option 3	0	82.35	0	2.50	2.59	2.50	97.56	86.82	97.56
Image differencing	0.00	98.93	0.98	0.60	1.19	0.60	99.99	2.13	99.02

Table 6. Accuracy results of the proposed system for the satellite image data sets

Alert Signal	Ground Truth					
	Flooded			Not flooded		
	Data Set #4	Data Set #5	Data Set #6	Data Set #4	Data Set #5	Data Set #6
High-strength alert	63	14	46	10	10	15
Medium-strength alert	7	5	15	4	2	18
No alert	25	31	7	516	562	524

Table 7. Accuracy assessment of the proposed system for flood detection

Method	Commission error (%)			Omission error (%)			Overall accuracy (%)		
	Data Set #4	Data Set #5	Data Set #6	Data Set #4	Data Set #5	Data Set #6	Data Set #4	Data Set #5	Data Set #6
Proposed method	16.67	40.63	31.58	4.62	5.23	5.11	93.76	92.96	92.48
Pixel-by-pixel method	90.12	84.95	29.24	3.86	5.29	1.89	83.27	88.48	95.6