AUTOMATIC DETECTION OF A REGION OF INTEREST IN A SATELLITE IMAGE

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ABSTRACT: A real scene observed from a satellite image contains a variety of features, textures and shadows and it can therefore be very complex to detect the region of interest (ROI). The ROI of a satellite image depends on the application field for Earth observation. Therefore image segmentation has been developed for extracting different features or textures inside an image. This can be performed a number of different ways using the image properties. Extraction of a feature of an image is very difficult to find the appropriate image segmentation techniques and combine different methods to detect the ROI most effectively.

This paper proposes techniques to classify objects in the satellite image by using image processing methods on high-resolution satellite images. The systems to identify the ROI are performed automatically and focus on the ROI of coastlines, forests, urban areas and agriculture. Three different methods to detect the ROI of the satellite images have been studied, implemented and tested; these are based on edge, histogram and texture segmentation. The edge method is based on edge detection and morphology. The histogram method is based on thresholding and morphology. The texture method is based on GLCM texture feature statistics and morphology. All three of the image segmentation methods can detect the ROI and reduce the size of the original image by discarding the unnecessary parts. A comparison of each technique has been performed. In this paper the combination of the proposed ROI automatic detection and image compression technique have been performed to find the percentage size reduction of the original image. Moreover the possibility to implement these techniques in cubesat onboard computer has been described. In addition the morphology structure element is used in these proposed techniques. A study on the appropriate shape and size of structure element is required and has been discussed in this paper.

1. Introduction

There is a continuing trend to develop satellites to be smaller and have better performance. The current development of cubesats aims towards improving its capability so that it can be used in more complex missions. There are many cubesats, with imaging instruments that provide high resolution remote sensing images. These instruments are producing increasingly large amounts of data. This increase requires more transmission time, power and memory on-board storage (Pablo et al, 2008). The challenge is how to store high quality images in space and transmit to the ground station within the limited resources available in a cubesat. The limitations of bandwidth transmission, power and storage on-board are significant issues in the design of cubesats.

As a consequence of all the above problems, one of the possible approaches is to reduce the size of the images produced by image segmentation techniques (Ye et al, 2008). Cubesats have the limitation of the power available onboard to transmit the images to the ground station. The ROI image can be compressed to reduce the size before sending to the ground station, which also benefits the power consumption for the cubesat. In this paper an image segmentation algorithm and image compression is described considering the limitations of the cubesat to decrease the on-board satellite image size that is suitable for adoption on a cubesat.

The rest of the paper is organized as follows: section 2 describes the proposed automatic detection of region of interest based on edge, histogram and texture segmentation. Section 3 presents the result of the experiments of the ROI automatic detection for three segmentation methods. Section 4 demonstrates the results of ROI and image compression technique to decrease the size of images. Section 5 present the results of the size and shape of morphological structure element. Section 6 demonstrates the hardware synthesis for the case study to implement the proposed system in the microcontroller, which is used for cubesat onboard computer. The final section gives a conclusion and identifies future work.

2. Automatic detection of Region of Interest

ROI detection has been applied in many areas, such as, telemedicine, remote sensing image, web browsing, image database and video compression, etc. (Rajkumar, 2001),(Fei, 2007), and (Chaoqiang, 2008). Identification of the ROI of an image can be performed using a manual or automatic process. There have been many studies to develop automatic ROI detection by using image segmentation techniques (Guamieri, 2002),(Oscal, 2007),(Guang, 2009), and (Shinji, 2005). A real satellite image can be very complex. Consequently, extraction of the required region of interest from within an image is very difficult using only one image segmentation technique. The solution is to use a combination of different image segmentation techniques to detect the region of interest effectively. There are many image segmentation methods, which are often based on basic properties of intensity values, discontinuity and similarity (Rafael, 2008),(Salem, 2010),(Cheng, 2001), and (Spirkorska, 1993). This paper identifies the suitable image segmentation techniques that can be used to detect the ROI of the satellite image automatically. There are three basic image segmentation techniques, which have been studied and tested.

2.1 Edge segmentation

The image segmentation based on edge segmentation method can be obtained by the detection of edges, defined by a change of the grey level intensity in a narrow area. The image is first converted from colour to greyscale (Rafael, 2008), and (Saravanan 2010). This process converts the brightness of each pixel to a grey level, which is usually consisted of 256 levels. This proposed segmentation process consists of two main techniques. Firstly, edge detection, based on finding the edges in an input image by approximating the gradient magnitudes of the image is used. Edges can be detected in many ways such as Laplacian, Roberts, Sobel and Gradient (Ali, 2001). The canny edge detection method was used in this module due to its performance. Secondly, the mathematical morphology technique helps to connect areas, which are separated by smaller spaces than that of the structuring element used. This technique fills image regions and holes and enables a boundary line to be identified (Zhang, 2009).

2.2 Histogram segmentation

The pixel values in an image can be represented by colour histograms. The concept of histogram segmentation is classifying an image using thresholds. The thresholding is performed by considering each peak of the histogram and mapping to a particular region by the concept of different intensities matching to different regions (Kurugollu, 2001). This research has determined groups of ocean, urban, forest and agriculture.

The thresholding is considered by each peak of the histogram and mapping to the region of object. Each thresholding is separated manually based on the information of the image. The thresholding is then applied to the image to convert to it to a binary image identifying pixels of interest and not of interest.

The next step is to apply dilation morphology and fill the holes of the image to get the ROI mask. The final step is to apply the ROI mask to the original image to extract the ROI image as the output image.

2.3 Texture segmentation

The Grey-Level Co-occurrence Matrix (GLCM) is widely used for texture measure in image analysis (Haralick, 1973). The textural features are based on statistics, which summarize the relative frequency distribution. This describes how often one grey tone will appear in a specified spatial relationship to another grey tone on the image of a certain distance and direction (Shanmugan, 1981), and (Soh, 1999),(Bartels, 2005). Haralick et al., first introduced the use of GLCM for extracting various texture features. The common statistics applied in texture analysis are energy, entropy, contrast, variance, homogeneity and correlation (Haralick, 1973). It has been used to determine texture similarity for grouping pixels in a region. Texture segmentation techniques generally consist of two stages. The first stage finds the local structure of an image and converts each pixel in the image into a vector of these local properties. Secondly the clustering method groups pixels which have similar properties together (Shervan, 2011).

There are many texture features that can extracted from GLCM. In this research the focus is on the five statistics Energy, Contrast, Correlation, Homogeneity and Entropy. The features extracted from the GLCM are used to classify the contents of an image. Energy describes the regularity of texture patterns. Contrast uses the difference of intensities as a weighting parameter for the probabilistic distribution. It increases when large difference of intensities occur with high probability. Correlation measures the uniformity of the distribution of the matrix, whereas homogeneity uses an inverse of the differences to signify the similarities of intensities. Finally entropy gives a measure of the degree of disorganisation of the image (Shanmugan, 198, De O., 2008).

3. The proposed ROI automatic detection techniques experiment and result

The ROI automatic detection process has been tested using three different types of segmentation techniques. The descriptions and results of each image segmentation techniques are described as follows.

3.1 Edge segmentation

The sample image is shown in figure 1. It is an image of the Great Lakes, located in North America. This image was taken by the ISS digital camera on 2006 (NASA, 2008). The process began with the conversion of the image to be the greyscale image, which is suitable for edge detection operation. Figure 2 illustrates the image after edge detection. Generally, the edge detection technique finds the lines of high contrast in the image. For this experiment, canny edge detection had been selected for use, because canny edge detection supports in filling of gaps at the detected edges.

Figure 1 Example input satellite image.

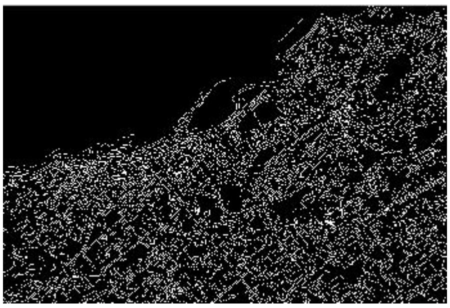


Figure 2 The result of edge detection step

The dilation of the greyscale image occurs to group nearby areas together by connecting edges that are near to each other. Whereas, if the edges have a long distance between them, this is the area that is called a hole in the image. These hole areas have many pixels that have a similar pixel value. The next step is the morphological filling of image region and holes. This process fills the holes in an image by detecting the area of dark pixels surrounded by white pixels. Figure 3 illustrates the image with the holes filled in. This has been performed by the process of morphological reconstruction in which there are repeated dilations of an image until there are no more changes. The technique is based on dilation, complementation and intersection for filling holes (Salem, 2010). The final step applies the ROI mask to the original image. The ROI mask and original image are compared with each other. The region of the original image, which is marked by the ROI mask, will be transferred to the final image. On the other hand, the region of original image which is marked by the non-ROI mask will be replaced by '0' for the final image. The output image of ROI automatic detection (figure 4) in the ocean area is a non-ROI, so it shown in white. The land is the ROI area and represents the original image. In this example image, the proposed edge segmentation ROI automatically reduces the size of the image to 76.34 % of the original image.

Figure 3 The ROI mask.

Figure 4 The output image of ROI detection

The proposed ROI automatic detection based on edge segmentation has identified the ROI of these images by edge detection and morphology processes. Table 1 shows that the size of the tested images are reduced on average to 66.70 % of the original. The various sizes and areas of the non-ROI leads to different image size reductions, for instance image-3 with a large amount of ocean in the image is reduced to 35.04 % of its original size.

3.2 Histogram segmentation

This segmentation process is based on the image grey-level histogram as shown in figure 5. The threshold for each group, e.g. ocean, urban, agriculture or forest needs to be selected automatically. The next step is to calculate the image thresholds and apply thresholding to each pixel of the original image. The input image is taken by a digital camera by the ISS crew in 2009 (NASA, 2009). The segmented image by histogram image segmentation is shown in figure 6, and this image can be converted to a binary image. After that dilation morphological is applied to connect areas and the holes. The output provides the ROI mask (figure 7). The final step applies the ROI mask to the original image as shown in figure 8.

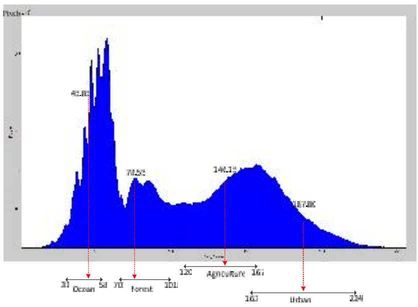


Figure 5 Input image

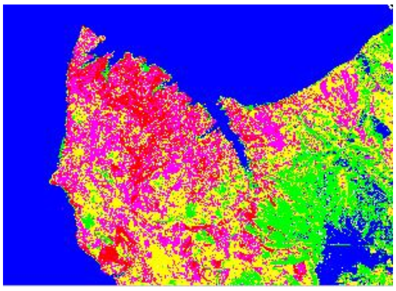


Figure 6 Histogram segmented image

Figure 7 ROI mask

Figure 8 ROI image

In this experiment, all pixels are replaced by the corresponding pixel value for that category. Table 1 shows the result of a set of satellite images tested. The histogram segmentation can reduce the image size to an average of 73.39 % of the original image to perform the process. The major drawback to threshold-based approaches is that they often lack the sensitivity and specificity needed for accurate grouping (Fengzhi, 2011). This image segmentation technique requires knowledge of the characteristics of the objects in an image so that the correct thresholds can be applied (Salem, 2010). The proposed ROI automatic detection based on histogram segmentation has identified the ROI of these images by histogram detection and morphology processes. Table 1 shows that the sizes of the tested images are reduced on average to 73.39 % of the original. The various sizes and areas of the non-ROI leads to different image size reductions, for instance image-3 with a large amount of ocean in the image is reduced to 61.71 % of its original size.

3.3 Texture segmentation

The texture segmentation technique has been implemented to segment the example image. The steps of this segmentation to obtain the ROI are; firstly convert the RGB image into a greyscale image. Secondly calculate the GLCM matrix. This experiment used a window size of 9 pixel, orientation 0 degree and distance 1 pixel. Thirdly calculate the statistic for the new pixel, which consists of Energy, Contrast, Correlation, Homogeneity and Entropy. Fourthly normalize the matrix image with the statistic features. The next step is to obtain the ROI mask by using grey thresholding. Finally apply the ROI mask to the input image. Figure 9 shows the greyscale image of Bridgetown, which is the capital city of the island of Barbados. This image was taken by the ISS digital camera (NASA, 2008). Figures 10-11 show the results of applying the texture features of Energy and Contrast respectively.

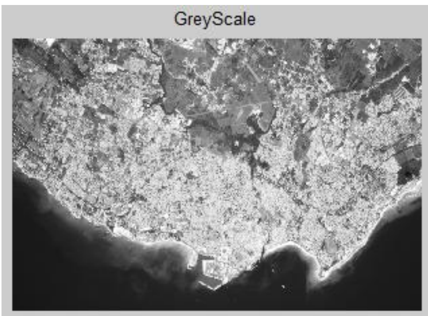


Figure 9 Greyscale image.

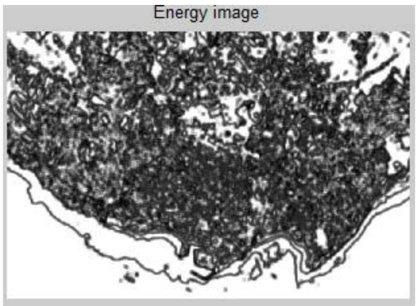


Figure 10 Energy features.

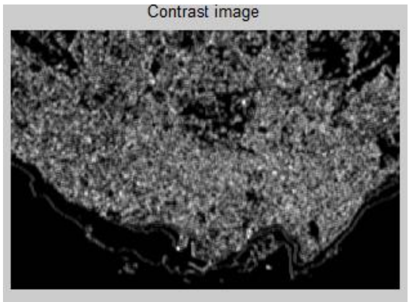
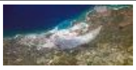


Figure 11. The result of ROI mark Figure 12. The ROI image. Figure 13. ROI image.

Using the GLCM to classify the texture features can be a suitable way to segment an image. Baraldi and Parmiggiani (1995) stated that ‘Two parameters, energy and contrast, are considered to be the most efficient for the discrimination of different textural patterns’ (Baraldi, 1995). The energy measures textural uniformly, which is the pixel pairs repetition and is high when the grey level distribution is constant or has a periodic form (Baraldi, 1995). In the example in Figure 10 the energy of the image shows that the image is possible to distinguish the ROI from the sea background. This paper uses the energy of the image in conjunction with morphological dilation to define the ROI of the image. Figure 12 shows the ROI mask applied after morphological dilation and Figure 13 is the output image after applying the ROI mask to the original image.

Table 1 shows the result of the application of the proposed texture segmentation algorithm to detect the ROI of the satellite images. These images show texture segmentation can reduce the image size on average to 73.00 % of original image. This method, therefore, is time consuming and this could potentially affect the power consumption (Haralick, 1973),(De.O, 2008), and (Baraldi, 1995). Power consumption and memory usage required to implement this technique in real hardware will be discussed in section 6.

Table 1 The proposed ROI automatic techniques experiment results.

Input image	Input size	Proposed system based on edge segmentation		Proposed system based on histogram segmentation		Proposed system based on texture segmentation	
		ROI image size	(ROI/Input) x100	ROI image size	(ROI/Input) x100	ROI image size	(ROI/Input) x100
1. 	3,207 KB	2,415 KB	75.30 %	2,446 KB	76.27 %	2,745 KB	85.59 %
2. 	3,988 KB	2,293 KB	57.50 %	2,104 KB	52.76 %	2,862 KB	71.77 %
3. 	10,184 KB	3,568 KB	35.04 %	6,285 KB	61.71 %	3,765 KB	36.97 %
4. 	3,381 KB	2,008 KB	59.40 %	2,382 KB	70.45 %	2,145 KB	63.44 %
5. 	13,426 KB	9,390 KB	69.94 %	9,957 KB	74.16 %	10,934 KB	81.44 %
6. 	12,685 KB	1,1847 KB	93.40 %	12,384 KB	97.63 %	11,674 KB	92.03 %
7. 	1,678 KB	1,281 KB	76.34 %	1,355 KB	80.78 %	1,338 KB	79.74 %

4. The ROI automatic detection and image compression

Reducing the size of the satellite image before transmitting it to the ground station is required to minimize the power consumption for transmission. In this section the combination of the ROI technique with the image compression based on biorthogonal wavelet image compression is presented. The result of the simulations are shown in table 2. On average over the seven images the proposed ROI detection based on the edge detection and image compression reduces the image size to 63.11 % of the original. The ROI detection based on histogram and texture segmentation decreases the size of satellite images to an average of 65.01 % and 66.06 % of the original respectively. Whilst the value of size reduction depends on the type of image the small differences indicate that all methods are equally good at identifying the ROI. In addition the experiment shows that the proposed ROI detection based on texture segmentation and subsequent image compression takes a considerably longer time (950.16 seconds) to compute compared to other segmentations that are around 7.12 and 14.36 seconds for edge and histogram segmentation respectively (test performed on Intel core 2 Duo CPU 3.16 GHz and RAM 4.00 GB).

Table 2 The proposed ROI automatic techniques and image compression experiment results.

Input image	ROI automatic detection and image compression									
		Edge segmentation and image compression			Histogram segmentation and image compression			Texture segmentation and image compression		
	Input size : A (KB)	ROI image size (KB)	Wavelet compressed : B (KB)	(B/A)x 100	ROI image size (KB)	Wavelet compressed : C (KB)	(C/A)x 100	ROI image size (KB)	Wavelet compressed : D (KB)	(D/A)x 100
1. 	3,207	2,415	2,375	74.06 %	2,446	2,394	74.65 %	2,745	2,520	78.58 %
2. 	3,988	2,293	2,149	53.89 %	2,104	1,978	49.60 %	2,862	2,367	59.36 %
3. 	10,184	3,568	3,330	32.70 %	6,285	4,230	41.54 %	3,765	3,676	36.10 %
4. 	3,381	2,008	1,934	57.20 %	2,382	2,066	61.11 %	2,145	2,045	60.48 %
5. 	13,426	9,390	8,079	60.17 %	9,957	8,321	61.98 %	10,934	8,439	62.86 %
6. 	12,685	11,847	11,343	89.42 %	12,384	11,186	88.18 %	11,674	11,322	89.26 %
7. 	1,678	1,281	1,247	74.31 %	1,355	1,309	78.01 %	1,338	1,272	75.80 %
Summary		Average reduction to 63.11%			Average reduction to 65.01%			Average reduction to 66.06%		

5. Morphology structure element study

The dilation technique which is implemented using this method gradually enlarges the boundaries of regions of objects. The dilation operator has two data inputs. The first one is the image and the second is the structure element which is defined by size and shape (Rafael, 2008). A considerable amount of research has been performed on the morphology of the structuring elements (Wang, 2009), and (Hedberg, 2009). The selection of structuring element size and shape depends on the geometric shapes that need to be extracted from the input image. For instance, for extracting shapes from geographic aerial images of a city, a square or rectangular element will provide good results (IDL, 2005).

The ROI image segmentation based on edge, histogram and texture segmentation have common techniques in their processes; the morphology dilation and the morphology fill regions and holes. The structure element (SE) is the main parameter used in the morphological technique for image processing. Hence it is necessary to understand how the shape and size of SE affects the output image of the proposed ROI automatic detection system.

This research has investigated the shape and size of SE selection to find an appropriate method for the proposed system. The different SE shapes have been tested to study the behavior of the proposed ROI detection. Table 3 illustrates the test results of different shapes of SE changing the output images. The results show the percentage of difference between the ROI automatic detection and manual detection by using different SE. The ROI image from square, diamond and disk SE give similar results. However the line shape cannot detect some information in the ocean and land that have large regions with similar pixel values.

Table 3: The percentage difference between the ROI automatic detection and ROI manual detection using different shapes of structure element.

SE shape	Square	Diamond	Disk	Line
ROI image				
Percentage difference	10.27 %	10.52 %	10.74 %	11.48 %

In addition four different sizes of the SE have been applied using the proposed system to test the effect on the resultant image as show in table 4. There are four different sizes varying from 5x5, 10x10, 15x15 to 20x20 pixels. Table 4 shows the ROI images which are produced by the proposed system based on edge segmentation using the square shape of 4 different sizes. The results show that the ROI mask using size 3 gives the smallest percentage of difference between ROI automatic detection and ROI manual (3.33%).

Table 4: The percentage difference between the ROI automatic detection and ROI manual detection using square shape in different sizes of structure element.

SE size	5 x 5	10x10	15x15	20x20
ROI image				
Percentage difference	5.60 %	4.44 %	3.33 %	4.38 %

6. The proposed system in hardware

In the real implementation on cubesat of the proposed system, which consists of ROI automatic detection and image compression methods, additional power would be required. To quantify this increase, a particular proposed system based on edge segmentation for ROI automatic detection has been studied. Table 5 shows the number of clocks that operators use to process the proposed system. The test has been applied to four different image sizes in order to find the relationship between the size of image and number of clocks to operate. The numbers of operators, multiply, pulse, divider and compare, are calculated from the data flow step by step of the ROI automatic detection and wavelet image compression. For example for an image size of 128x128x3, the total number of clocks is around 75 million. From this result, the estimation of the power consumption can be calculated. If a cubesat uses Atmel ARM7 which operates at 40 MHz, it uses a power of 754.09 mW. Many cubesat projects have used COTS processors. For example the Atmel ARM7 and PIC 16F877 flight module board have been used in AAUsat-II and CubeSatXI-IV respectively (Teney, 2009). The appropriate microprocessor implementation is dependent on the mission requirements.

Table 5 The summary of the number of operators used for the proposed algorithm in four different sizes of image.

Image size	Number of clocks to operate the proposed system				Total number of cycles	Microcontrollers	
	Multiply	Pulse	Divider	Compare		Arm7 300 mW @ 40 MHz	PIC 16F877 10 mW @ 4 MHz
1. 16x16	960,528	200,296	216	5,120	1,166,160	11.66 mW	2.92 mW
2. 32x32	3,842,064	829,384	216	20,480	4,692,144	46.92 mW	11.73 mW
3. 64x64	15,368,208	3,373,960	216	81,920	18,824,304	188.24 mW	47.06 mW
4. 128x128	61,472,784	13,608,712	216	327,680	75,409,392	754.09 mW	188.52 mW

7. Conclusion

This paper proposes techniques to reduce the size of the satellite image onboard spacecraft by using ROI automatic detection technique and image compression. The limitations of bandwidth, transmission power and storage on-board are significant constraints on the scope to develop the capability of a cubesat. The system consists of two main parts; ROI automatic detection module and image compression module.

The ROI automatic detection is a method to define the area of an image that contains information of interest. Three different methods to detect the ROI of the image have been studied, implemented and tested; edge, histogram and texture segmentation. The edge method is based on edge detection and dilation morphology. The histogram method is based on automatic thresholding and dilation. Whereas, the texture method is based on GLCM texture feature statistics and dilation morphology. All three of the image segmentation methods can reduce the size of the original image by discarding the unnecessary parts in the image and retaining the important parts (ROI) of the original image. This ROI automatic detection can reduce the original image size ranging from 10% to 80%, the difference depending on the characteristics of the original images. If the input image consists of large areas of similar pixels this results in few edges being detected, this image will have a large non-ROI area. Consequently the output image has a small ROI and data is considerably reduced. With the histogram ROI detection, if the image has large areas that have similar or approximately close values, these pixels will be classified into the same group of objects. After performing the grey thresholding, the image can separate the ROI and non-ROI areas. Whereas, the texture segmentation will give the energy of the image, where grey thresholding can be applied for detecting the edges of the image and then dilation morphology can be applied to classify the area of ROI. From results of computation time it was found that the texture segmentation is the most time consuming compared to the edge and histogram detection. A smaller processing time equates to less power usage in space. The edge segmentation was found to require the least time to process.

The image compression module implemented also further reduces the image size. The results show that the proposed system can reduce the size of the original satellite image, although the amount of decrease depends on the characteristics of the original image. The idea is to combine the ROI technique with image compression to reduce the data that is required to be transmitted to the ground station. In addition the size and shape of the morphological structure element used has been found to affect the output image size. Therefore future work is to compare the results of the proposed automatic ROI system to a manual process in more detail, and also how to identify small and specific ROI in an image, for example a rice field or specific patch of land.

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