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COMPARISON OF DIFFERENT EDGE DETECTION ALGORITHMS FOR SHORELINE BOUNDARIES EXTRACTION USING RADARSAT SAR IMAGERY

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Abstract : This paper presents work on extracting shoreline boundaries from Radarsat Synthetic Aperture Radar [SAR] imagery for shoreline mapping. Shoreline boundaries extraction from SAR data belongs to the boundaries detection problem in the field of image processing, in which image segmentation and edge detection algorithm are two conventional techniques to the boundaries detection.

SAR data is generally interrupted by speckle. The presence of speckle makes edge detection algorithm in SAR data difficult and image segmentation inadequate. For the purpose of this study, the edge detection algorithm was utilized. Several edge detection algorithms (Sobel, Prewitt and Canny) were applied on Radarsat SAR imagery and compared for their ability on extraction of shoreline boundaries along the Kuala Terengganu shoreline, Malaysia. The Gamma filter was used for removing speckle on Radarsat SAR image and Gamma filter size 7x7 provided the best result.

In this study, we proposed a combination of Canny edge detection algorithm with Thinning algorithm for the best extracting concave shoreline from Radarsat SAR imagery. It can be concluded that Canny algorithm has capability for shoreline extraction from Radarsat SAR imagery without involving further processing analysis and it can be determined the true water/land boundaries.

KEYWORDS: Edge detection algorithms, Shoreline boundaries, Radarsat SAR Imagery

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Introduction

Coastal zone monitoring is an important task in national development and environmental protection. Extraction of shoreline is the fundamental work which is necessary for coastal zone development and environmental protection. The coastal zone encompasses an area that extends seaward to the continental shelf and landward to the edges of tidal influence. One of the most serious limitations in utilize of satellite data particularly from passive and optical remote sensing system in these regions is the cloud cover problem such as coastal of Terengganu. Taking into account that the optical sensor is insufficient to provide information throughout the year, the use of SAR data was necessary. In order to capture the time and space dynamics of the coastal environment, Earth observation satellites have become vital components for shoreline mapping. Earth observation satellites, such as Radarsat, offer frequent data acquisition, fast delivery schedules, and a range of imaging options. Radarsat satellite represents a new tool to monitor the coastal zone and is possible for applications where customary optical stereoscopic have met with limited achievement. SAR satellite for shoreline extracting has potential advantage over conventional optical stereoscopic techniques, it can go through cloud and darkness to obtain images in areas where obtaining images using traditional sensor was often difficult or impossible (Gordon et al., 1998; Dellepiane et al., 2004).

Edge detection algorithm is one of the important and ridges technique in many image processing applications such as objects recognition and boundaries detection. Canny formulated edge detection as an optimization problem, especially for two-dimensional image. Canny edge detector can give the edge information of both intensity and direction. Canny edge detection algorithm is capable of detecting and extracting edge fast with good precision (Canny, 1986).

According to Gonzalez and Woods (1992) and Parker (1997) technically, edge detection technique emphasizes the first property for shoreline extraction from satellite imagery and image segmentation technique is conceptually based on the second property. Because of the frequent lack of consistent, sufficient intensity contrast between land and water surfaces and complexity in individual shoreline boundaries from other object borders, edge detection technique makes comparatively easy to performance than image segmentation technique. Shoreline boundaries extraction from SAR data seems to be a simple application of remote sensing data, but delineate real boundaries between the land and sea surfaces from SAR data can become more difficult due to wind induced surface roughness on the water, which reduces the contrast between the land and water at the border between them. In order to extract real shoreline boundaries by traditional methods are inefficient through SAR data (Lee and Jurkevich, 1990; Mason and Davenport, 1996). The aim of this study is to extract real shoreline boundaries from Radarsat SAR imagery for shoreline mapping.

Study Area

The study area is located along the coastline of Kuala Terengganu, on the East coast of Peninsula Malaysia. This area is facing the South China Sea between Batu Rakit [561920 N, 602741 E] and Seberang Takir [571215 N, 591806 E], approximately 14.50 km (Figure 1).

This area lies in an equatorial region dominated by two monsoon seasons. The southwest monsoon lasts from May to September while the northeast monsoon lasts from October to March. The monsoon winds affect the direction and magnitude of the waves.

The maximum wave height during the northeast monsoon is larger than 3 m. The minimum wave height is found during the southwest monsoon, which is less than 1 m. The mean annual temperature lies in the range of 25.6°C and 27.8°C. The temperatures of surface water are typical of tropical type, being 27°C to 28°C (Rosnan, 1987).

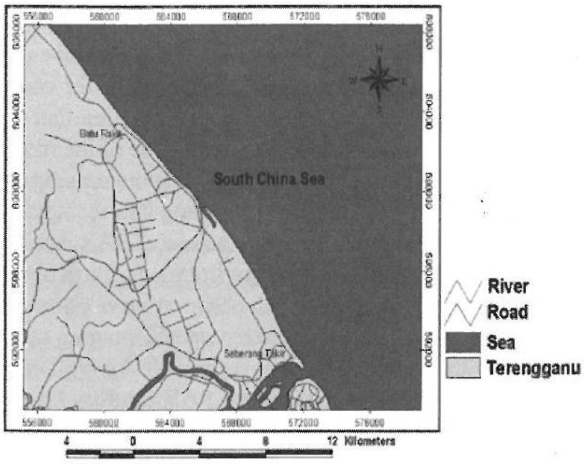

Figure 1: Study Area

Materials and Methods

Data Acquisition

There are two types of data used in this study: remotely sensed data and ground data. The remote sensing data used is Radarsat-1 SAR data and the ground data used is DGPS data.

In this study, a Fine [F3] range of beam modes Radarsat image with spatial resolution of 12 m taken on April 2nd 2004 has been analyzed. The image was acquired from Malaysian Center of Remote Sensing [MACRES]. F3 has incident angles between 41° and 44°, which is equivalent to 50 km swath width. Radarsat is a C-band [5.3 GHz frequency or 5.6 cm wavelength] system operating with HH polarization.

The ground data was collected from 2nd to 3rd September 2005. DGPS was used to track along the shoreline boundaries of Kuala Terengganu, between Batu Rakit and Seberang Takir.

Data Analysis

Data analysis involves image processing and GIS analysis for assessing the capability of shoreline extraction technique and identifies the performance of each algorithm by using Radarsat-1 SAR imagery and DGPS ground data measurement. Data processing for the image processing and GIS analysis procedure are shown in Figures 2 and 3.

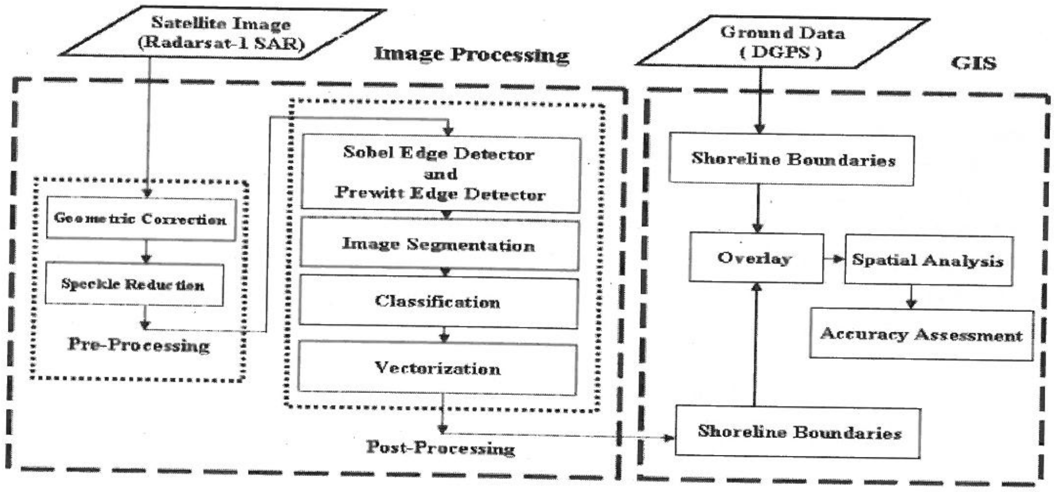

Figure 2: Methodological flowchart of Sobel and Prewitt algorithms for shoreline boundaries extraction

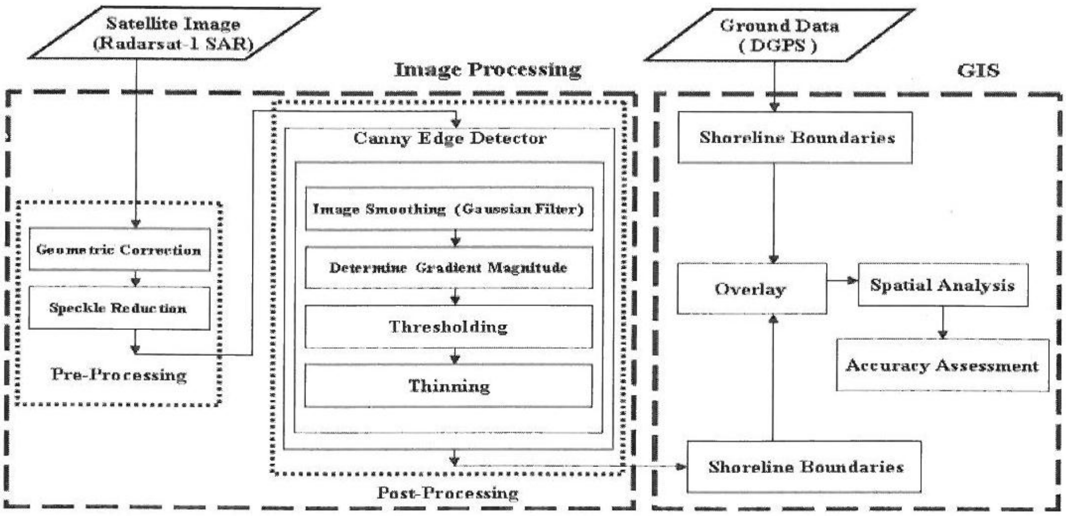

Figure 3: Methodological flowchart of Canny algorithm for shoreline boundaries extraction

Image Pre Processing

Pre processing of Radarsat-1 SAR image for preparing post processing contains geometric correction and speckle reduction.

Image-to-image registration technique was utilized to correct data before further data manipulation and analysis were done. The geometric correction is a vital part of pre processing, as it will determine the accuracy of shoreline boundaries positioning. The lower the RMS error, the better the fit of transformation to the ground control points. In this study, less than 0.3 pixel of RMS error was achieved.

SAR data is generally corrupted by a signal dependent non-additive noise called speckle so without speckle rejection is not possible to extract any useful feature. Many researchers (e.g. Shi and Fung, 1994; Oliver and Quegan, 1998; Anton and Sanden, 2000) proposed Gamma filter as the most successful filter for removing speckle filtering on the SAR imagery without the blurring the major edges features. In this study, the speckle reduction was done based on Gamma filter analysis. The algorithm was based on the study of Lopes et al. (1990, 1993) using the structure detection and statistical adaptive speckle filtering in SAR imagery. Gamma algorithm was applied to implement spatial filtering on every individual pixel in an image via the grey level values in a square window surrounding every pixel. The size of the filter must be odd, and can be from 5 x 5 to 9 x 9 kernel windows size. For amplitude image, every grey level was squared and square root will be applied to the last result. For removing isolated pixel that is very low value or very high in homogeneous area all pixels were filtered. In order to filter pixels situated near the edges of the image, edge-pixel values were replicated to provide sufficient data.

The grey level value, R from algorithm for the smoothing pixel was calculated as follows:

$$R = \begin{cases} I & if C_i \leq C_u \\ \dfrac{B * I + \sqrt{D}}{2 * \alpha} & if C_u \langle C_i \langle C_{max} \\ CP & if C_i \leq C_{max} \end{cases} \quad (1)$$

$$C_u = \frac{1}{\sqrt{N_{look}}} \quad (2)$$

$$C_i = \frac{\sqrt{Var}}{1} \quad (3)$$

$$C_{max} = \sqrt{2} * C_u \quad (4)$$

Where:
R = Pixel value
N look = Number of looks
Var = Variance in filter window
CP = Center pixel value
I = Mean pixel value in the filter window

$$\alpha = \frac{(1 + C_u^2)}{(C_i^2 - C_u^2)} \quad (5)$$

$$B = \alpha - N_{look} - 1 \quad (6)$$

$$D = I^2 * B^2 + 4 * \alpha * N_{look} * I * CP \quad (7)$$

Edge Detection Algorithms

Post processing for extraction of shoreline boundaries from Radarsat-1 SAR imagery consists of tree main algorithms such as Sobel, Prewitt and Canny edge detection algorithms.

Sobel and Prewitt edge detection algorithms generate an image where higher grey level values specify the attending of an edge between two objects. The Sobel and Prewitt operator carry out a 2-D spatial gradient dimension on an image and consequently emphasizes regions of high spatial frequency that correspond to edges. Characteristically, these algorithms used to get the estimated complete gradient magnitude at every point in an input greyscale image. These algorithms are one of the most popular classical edge detectors.

The Sobel and Prewitt algorithms are use two templates with different kernel windows size (3 x 3 and 7 x 7) to compute the gradient value. According to Gonzalez and Woods (1992), templates with 7 x 7 kernel windows size required more computations and tended to blur the edges slightly. Therefore in this study, templates 3 x 3 kernel windows size were used. Algorithms of Sobel and Prewitt are showed as (Gonzales and Winz, 1977; Sobel, 1978; Davies, 1990).

Templates of Sobel edge detection with 3 x 3 kernel windows size:

$$X = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} Y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$\begin{matrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ a_7 & a_8 & a_9 \end{matrix}$$

Where $a_1 \ldots a_9$ are the grey levels of every pixel in the image. The partial derivatives of the Sobel operator are computed for the center pixel [a_5] as below:

$$G_X = -1*a_1 + 1*a_3 - 2*a_4 + 2*a_6 - 1*a_7 + 1*a_9 \quad (8)$$

$$G_Y = 1*a_1 + 2*a_2 + 1*a_3 - 1*a_7 - 2*a_8 - 1*a_9 \quad (9)$$

The gradient magnitude is specified by:

$$\text{Sobel gradient} = \sqrt{G_X^2 + G_Y^2} \quad (10)$$

The Prewitt edge detection algorithm is very similar to the Sobel edge detection algorithm with difference but templates structure. Templates of Prewitt edge detection:

$$X = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} Y = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

The partial derivatives of the Prewitt operator are computed for the center pixel [a_5] as below.

$$G_X = -1*a_1 + 1*a_3 - 1*a_4 + 1*a_6 - 1*a_7 + 1*a_9 \quad (11)$$

$$G_Y = 1*a_1 + 1*a_2 + 1*a_3 - 1*a_7 - 1*a_8 - 1*a_9 \quad (12)$$

The gradient magnitude is specified by:

$$\text{Prewitt gradient} = \sqrt{G_X^2 + G_Y^2} \quad (13)$$

In order to filter pixels situated near the edges of the image, edge-pixels values are replicated to provide sufficient data.

The Canny algorithm employs more mathematics than the simple edge detection algorithm, and modifying the setting can improve the results (Canny, 1986).

According to Ding and Goshtasby (2001), the non-maxima suppression of Canny edge detector is not able to extract concave edges as the image. The non-maxima suppression of Canny edge detector will miss many concave edges from the image. To overcome this problem, we employed a combination of Canny edge detection algorithm and thinning algorithm for the best extracting concave edges shoreline from Radarsat SAR imagery.

To summarize, the algorithm of Canny in this study follows the steps below (Canny, 1986; Ding and Goshtasby, 2001; Jain et al., 1995).

1. Smooth the image with an appropriate Gaussian filter to reduce desired image details and noise.
2. Calculate the gradient magnitude and gradient direction at each pixel.
3. Utilize hysteresis thresholding technique for removing the weak edges from the image.
4. Employ Thinning algorithm on the binary edge image to produce pixel wide skeleton curves. Subsequently a sequence of pixels for each curve is extracted from the image. An extracted pixel curve is converted to vector form by fitting piecewise line segments to it.

GIS Analysis

In order to quantify the capability of shoreline extraction technique and identifies the performance of each algorithm of Radarsat SAR imagery and DGPS ground data, GIS technique was applied. The GIS analysis was performed using two main application packages, Arc GIS 8.3 and ArcView GIS 3.2.

Results and Discussion

One of the important steps of pre processing is speckle reduction before performing post processing on the satellite imagery. The presence of speckle not only reduces the interpreter's ability to resolve fine detail, but also badly disturbs the extraction and interpretation of the information of the objects. Therefore, speckle reduction is an important and essential procedure for Radar image processing. To preserve the precise position of the shoreline, an edge-preserving operator is required to remove the image noise.

Figure 5 shows the image after Gamma filter 7 x 7 kernel windows size and it shows that has been reduced high frequency noise or speckle. Gamma filter has different kernel windows size, the dimensions of the filter can be from 5 x 5 to 9 x 9. Different filter size will significantly affect the quality of processed images. If the filter is large, delicate detail of the image will be lost in the filtering process. If the filter is too small, the speckle filtering is not well effective.

Gamma filter 7 x 7 kernel windows size provided the best results without losing the image spatial information compared to the other kernel windows size. This result agreed with the previous study by Anton and Sanden (2000); Masoud Karamali et al. (2005). This is due to the fact that a good speckle noise filter should preserve the mean backscattering coefficient value of homogeneous areas. It is to say that the filter should be unbiased estimation. From the above results, it can be stated that the Gamma filter 7 x 7 kernel windows size not only restrain the speckle noise very well, but also preserve the precise position of the shoreline.

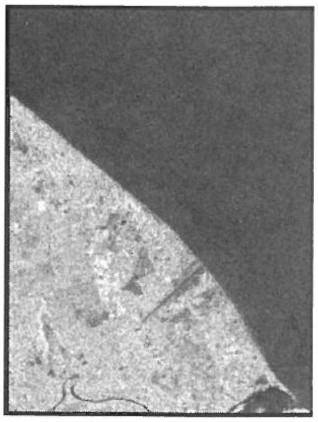

Figure 4: Original Image

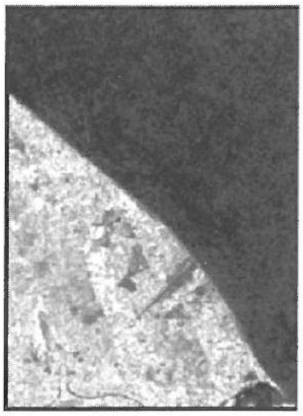

Figure 5: Gamma filter 7 x 7 kernel windows size

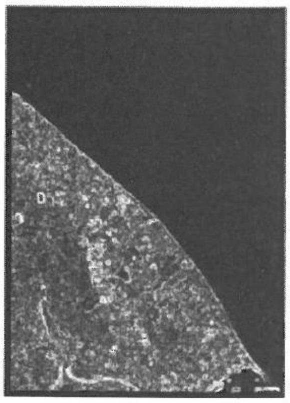

Figure 6: Sobel algorithm

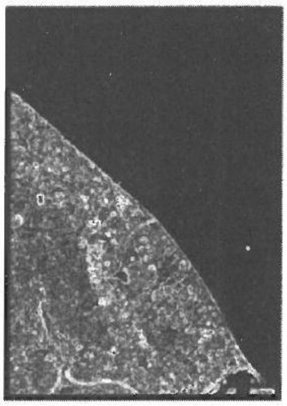

Figure 7: Prewitt algorithm

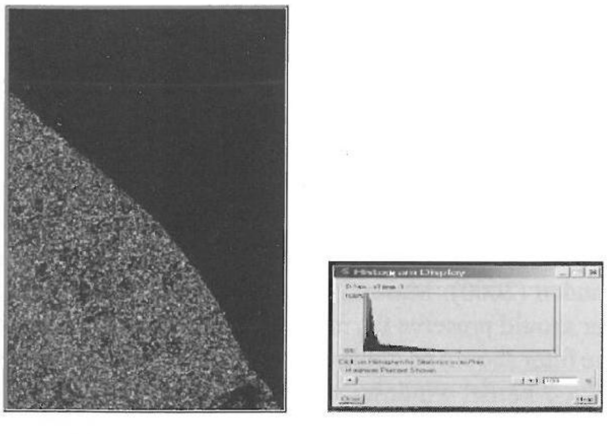

Figure 8: Image segmentation and grey level histogram of Sobel algorithm

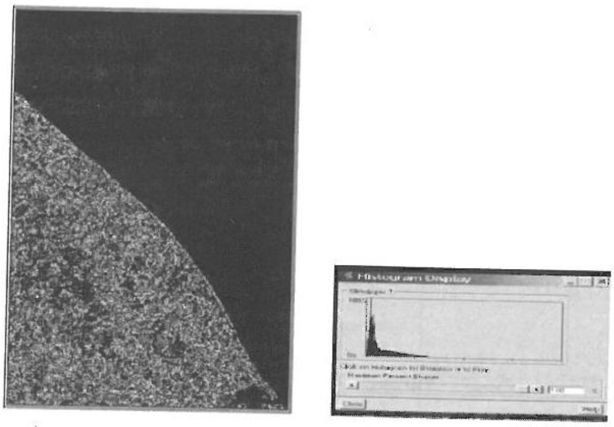

Figure 9: Image segmentation and grey level histogram of Prewitt algorithm

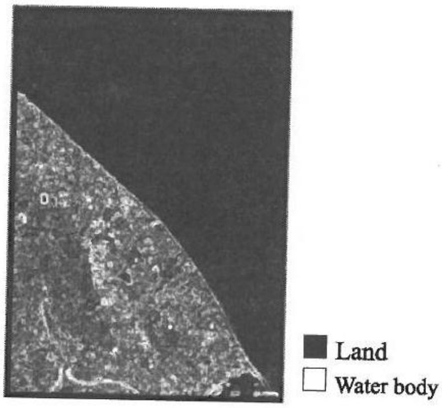

Figure 10: Unsupervised classification of Sobel algorithm

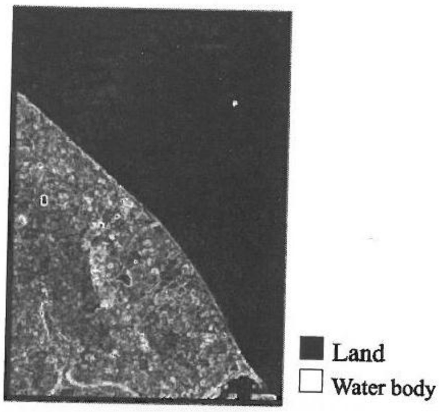

Figure 11: Unsupervised classification of Prewitt algorithm

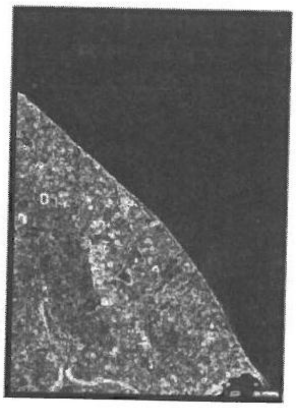

Figure 12: Vector edges layer image of Sobel algorithm

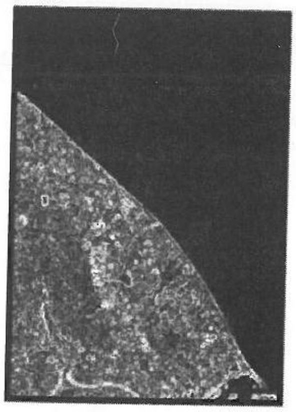

Figure 13: Vector edges layer image of Prewitt algorithm

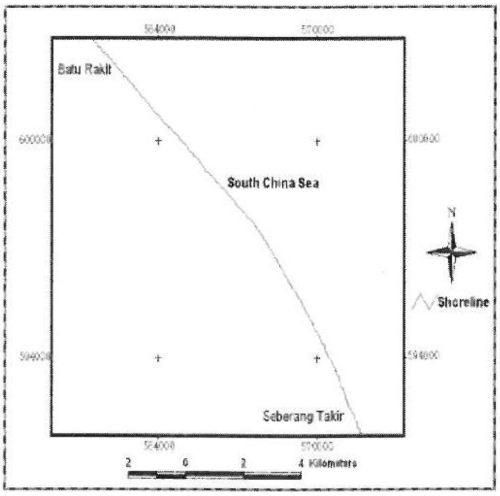

Figure 14: Shoreline extracted from Sobel algorithm

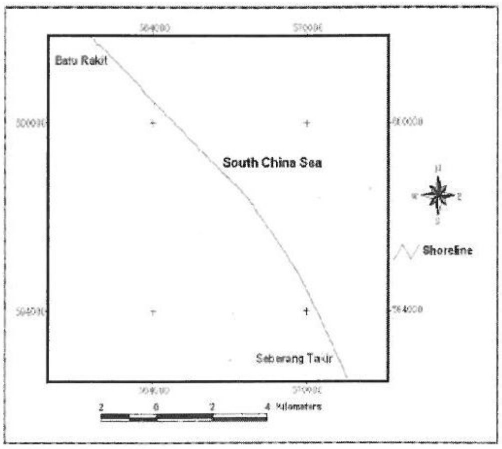

Figure 15: Shoreline extracted from Prewitt algorithm

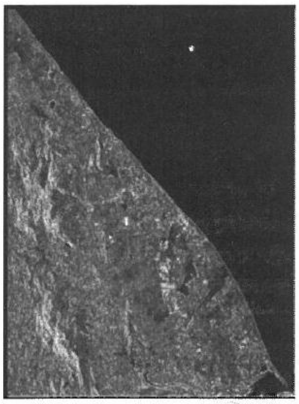

Figure 16: Canny algorithm

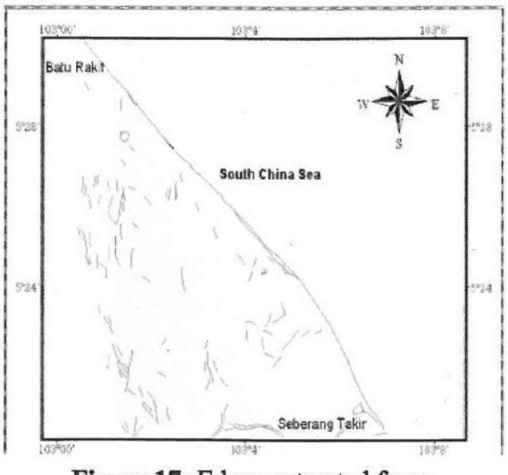

Figure 17: Edges extracted from Canny algorithm

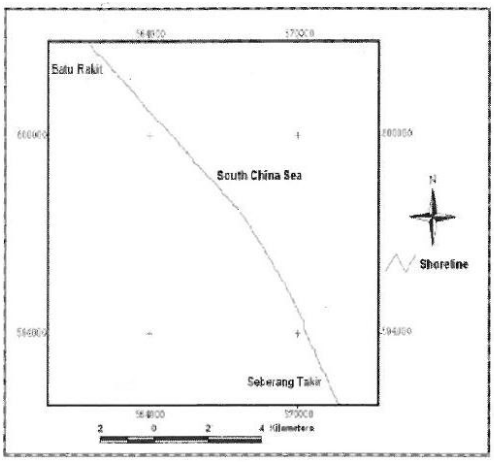

Figure 18: Shoreline extracted from Canny algorithm

Sobel and Prewitt algorithms have limitations when dealing with noisy images, and these algorithms are, however, sensitive to the effects of noise. Hence, it is possible that the non-normality of noise can adversely affect the performance of Sobel and Prewitt edge detectors. Furthermore, they involve further processing analysis such as image segmentation and classification for shoreline extraction from SAR imagery as have been shown in Figures 6, through 15. Therefore, the run time of processing analysis was long. Referring to Figures 6 and 7, it can be seen that the edges detected by Sobel and Prewitt edge detection are very thick and there are some false edges. In addition, they produce very weak response to concave edges from Radarsat SAR image, unless edges are very sharp. Therefore, Sobel and Prewitt algorithms are not suitable to extracting shoreline boundaries from Radarsat SAR imagery.

The Canny edge detection technique preserves the edges of object, and can be very useful for coastal erosion studies. Referring to Figures 16 and 17, the Canny algorithm can provide an automatic digitizing for shoreline boundaries from Radarsat SAR imagery. The performance of Canny detector for extracting shoreline vector from the Radarsat SAR imagery has been shown in Figures 17 and 18. It is obvious that Canny algorithm has the capability for shoreline extraction on Radarsat SAR imagery without involving further processing analysis.

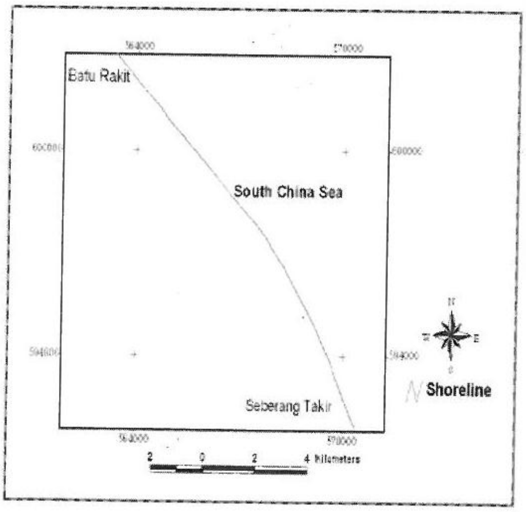

Figure 19: Shoreline extracted from DGPS

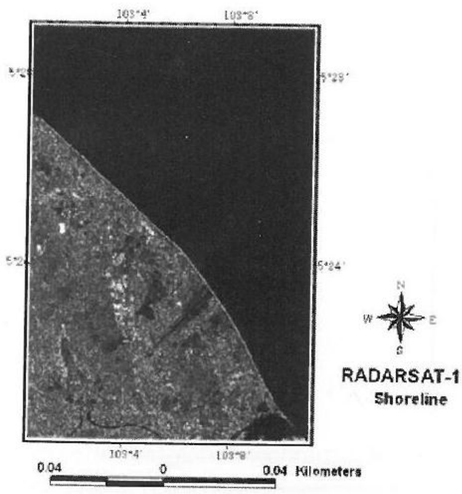

Figure 20: Shoreline from DGPS overlaid with SAR imagery

Figure 19 shows extracted shoreline using DGPS and Figure 20 shows overlaid DGPS data on the Radarsat SAR imagery. Result shows that shoreline boundaries are fit to DGPS data and the changes in shoreline are not more obvious through time duration between DGPS data collection and satellite imagery.

Finally, the capability of shoreline extraction technique and the performance of each algorithm on the Radarsat SAR imagery is specified by overlaying two vector layers of shoreline boundaries from ground data measurement of DGPS and satellite data as shown in Figures 21 through 26.

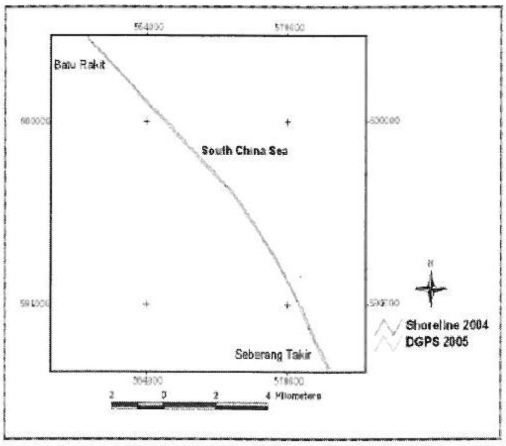

Figure 21: The comparison of shoreline extracted using Sobel algorithm and measured by DGPS

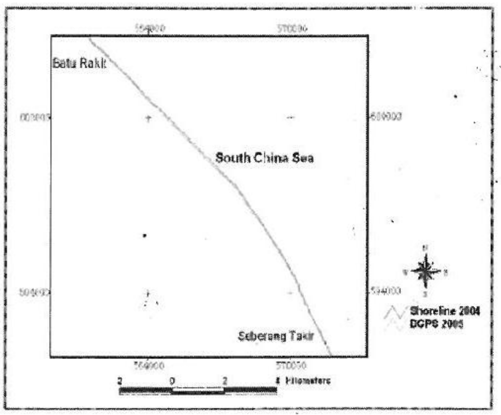

Figure 22: The comparison of shoreline extracted using Prewitt algorithm and measured by DGPS

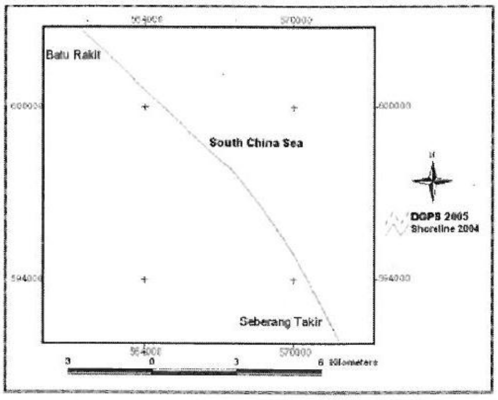

Figure 23: The comparison of shoreline extracted using Canny algorithm and measured by DGPS

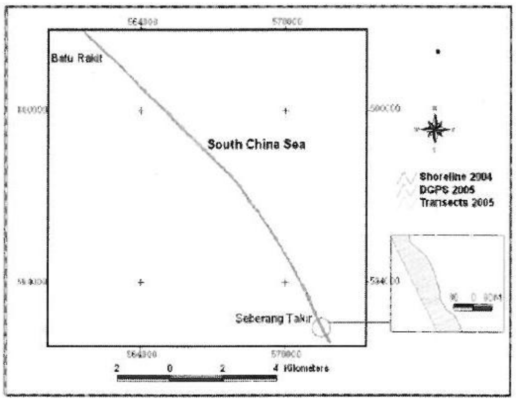

Figure 24: Transect lines from Sobel algorithm

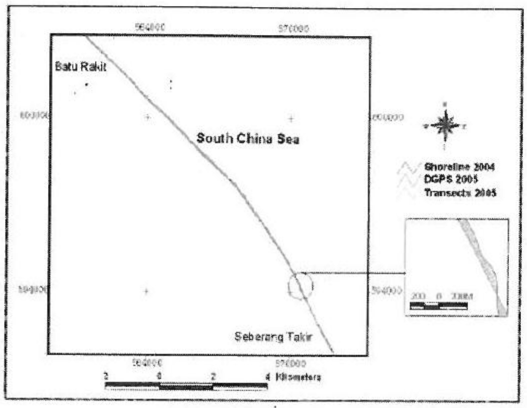

Figure 25: Transect lines from Prewitt algorithm

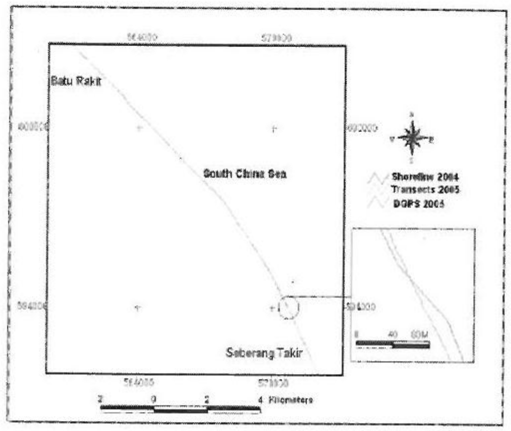

Figure 26: Transect lines from Canny algorithm

Different edge detection algorithm such as Sobel, Prewitt and Canny algorithms provided different information.

Table 1: Statistical assessment from algorithms

Algorithm	Mean (m)	Max (m)	Min (m)
Sobel	58.9	115.9	7.5
Prewitt	45.9	88.2	-59.1
Canny	5.7	26.9	-12.6

Table 1 illustrates the performance of different shoreline extraction technique. Results show that shorelines extracted from Sobel, Prewitt cannot be considered as significant results because the beach was not dramatically changed for 17 months. This is clearly visible along the coast of study area. The results show the shoreline extracted from Canny algorithm is similar to the logical than other results. According to many research studies, the Terengganu coastal is a highly dynamic and complex environment characterized via a multitude of processes and activities. Anyhow, the result of Canny algorithm is analogous to the studies done by Maged (2000 and 2001) at the same study area. Maged utilized ground data and remotely sensed data to detect shoreline change along the Kuala Terengganu shoreline, Malaysia. The ground data included ship observations data, oil platform data and fieldwork. The remotely sensed data included Radar data and optical data. The rate of shoreline change varied between the sources of data. Finally, Maged reported that the average rate of shoreline change along the Terengganu coastline is less than 2 metres per year.

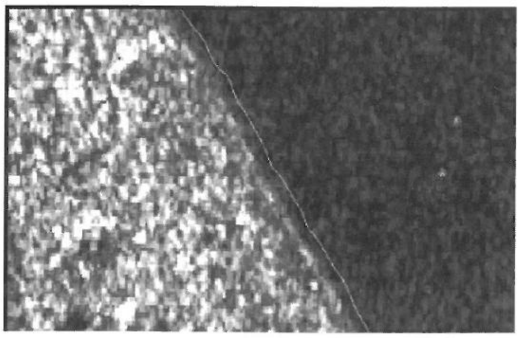

Figure 27: Zoomed window from Sobel

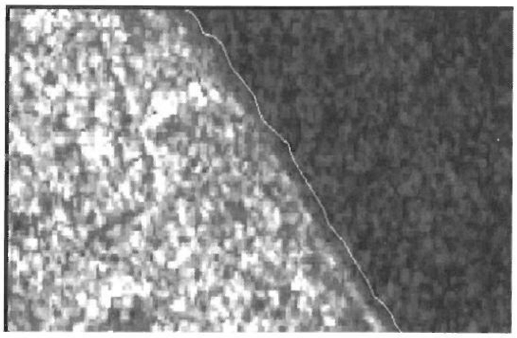

Figure 28: Zoomed window from Prewitt

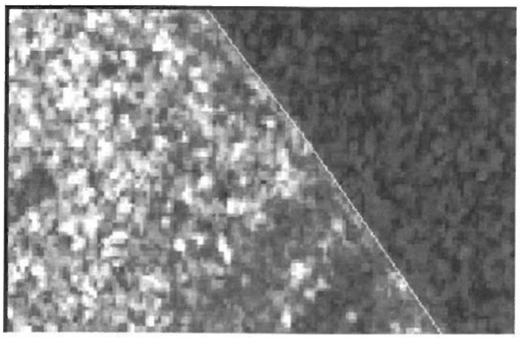

Figure 29: Zoomed window from Canny

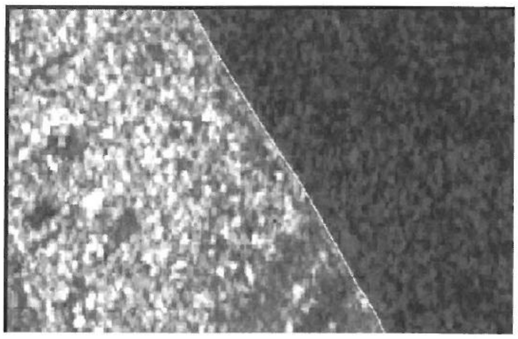

Figure 30: Zoomed window from DGPS

The presence of speckle noise and the strong signal return from a wind roughened, wave modulated water surfaces reduce the contrast between the water/land boundaries in SAR data. Consequently, it is difficult to extract the real shoreline boundaries from SAR data via conventional techniques such as classical edge detection algorithms, image segmentation and classification similar to the actual image as show in Figures 27 and 28. This means that results of Sobel and Prewitt are in good agreement with the previous study Lee and Jurkevich (1990).

Referring to Figures 18-20, and Figures 23, 26, 29 and 30, the Canny algorithm provides a good detection of linear and concave features in Radarsat images as similar to the real image. It is obvious that the Canny edge detection algorithm can give more information about features of land and its border with water body by determining the true water/land boundaries. This finding is in agreement to the studies by Jezek and Liu (2004), Masoud Karamali et al. (2005) and Masoud Karamali (2006).

Referring to Figures 18-20 and Figures 23, 26, 29 and 30, the Canny edge detection algorithm can extract the concave shoreline on the Radarsat images. This is obviously demonstrated along the Kuala Terrengganu shoreline, as this area tends to be concave shoreline.

Conclusion

Radarsat represents a new instrument for coastal zone monitoring and is viable for applications where traditional optical sensors have met with limited success. Radarsat is equipped with a synthetic aperture Radar [SAR] sensor, which provides its own source of illumination; thus, Radarsat SAR for shoreline detection has potential advantage over conventional optical stereoscopic techniques. Yet, it can infiltrate darkness and any weather condition to get images, particularly in this study area where obtaining images using traditional sensor was often difficult.

Results from this study showed that the shoreline boundaries detection technique can be easily implemented by using the edge detection concept based on the Canny algorithm from Radarsat SAR imagery.

It can be concluded that Canny edge detection algorithm can be used as automatic tools for shoreline boundaries detection from SAR data. It is obvious that Canny algorithm can extract the concave shoreline boundaries along the shoreline of Kuala Terengganu, Malaysia.

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