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A REVIEW ON SHORELINE DETECTION BASED ON SATELLITE IMAGERY

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ABSTRACT

Sea level rise is one of the main factors that affects the shoreline, which directly will affect its surrounding activities. Thus, it is important to observe the shoreline level, mainly for mitigation purpose. However, manual inspection and field work require extensive amount of effort, time and money. Therefore, satellite imagery has been widely used to observe the shoreline variability so that estimation can calculated based on past data. There are various techniques of shoreline detection which depend on the application. In this paper, some popular methods of shoreline detection were discussed such as pixel swapping, active contour and artificial neural network. The most challenging issue in processing satellite imagery is the computational burden. In a nutshell, shoreline detection technique should be selected based on the required application due to timing constraint.

Keywords: shoreline detection, satellite imagery, pixel swapping algorithm, active contour.

INTRODUCTION

Shoreline is the boundary line between land and sea water that constantly change due to active environmental factors. The main causes for shoreline change are erosion and sea level rise. Erosion is usually due to waves, tides, winds, and periodic storms (Van & Binh, 2008). Shoreline change will affect human lifestyle, cultivation and waterway transportation activities. Hence, shoreline analysis is important to know the present and past locations, so that it can be predicted in the future for environmental surveillance and coastal organization (Van & Binh, 2008). Output of the analysis can be used in many ways such as in designing coastal protection, assessment of sea-level rise, development of hazard zone and many more (Boak & Turner, 2005).

There were four techniques as described by Tran Thi Van *et al.* (2008) to capture the shoreline shape variation which are defined by its advantages and disadvantages (Boak & Turner, 2005) as following: (1) manual inspection and field works give the best measurement of the actual land usage loss, but the estimation requires considerable amount of time, effort and money; (2) recent altimetry technology by using radar or laser of altimeters, but the detectors are currently expensive and hard to obtained; (3) pictorial information given by airborne imagery evaluation is enough but sampling frequency is low, time consuming and expensive.; (4) digital imagery in infrared spectral bands that comes from multispectral remote sensing. Its main advantages are fast sampling, inexpensive and large ground coverage monitoring (Van & Binh, 2008).

SATELLITE IMAGERY

Recent trend shows that satellite imagery has become widely available at reasonable price because of more parties have involved in supplying the database coupled with the application software. There are four types of satellite imagery resolution, which are spatial, spectral, temporal and radiometric (Campbell, 2002). Spatial resolution represents the ability of the instruments to detect and distinguish small objects and fine details in a larger object. While, spectral resolution is defined as the ability of a sensor in terms of number of bands in the electromagnetic radiation spectrum. The sensitivity to small radiation differences of the observed object (e.g. level of brightness) is referred as radiometric resolution. Lastly, temporal resolution stands for the total time that an imagery has been exposed in a certain plane position.

One of the earliest good remote sensing data can be obtained from The Satellites Pour I'Observation de la Tenre (SPOT), which was introduced by a collaboration between France, Belgium and Sweden in 1978. While, Land Observation Satellite/Sensor, also known as LANDSAT program started in 1972 are able to give extensive continuous global record of land cover images. The details about these two satellite imageries can be obtained at http://carpe.umd.edu/geospatial/satellite_imagery_resources.php and http://www.nrcan.gc.ca/earth-sciences/geomatics/satellite-imagery-air-photos/satellite-imagery-products/educational-resources/9375 as summarized in Table-1 and 2.

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Table-1. Type of satellite imagery and its corresponding sensors.

Type		Launched	Sensor
SPOT	SPOT 1 SPOT 2 SPOT 3	1986 1990 1993	2 Visible Wavelength High-Resolution (VHR)
	SPOT 4	1998	2 Visible Wavelength & Infrared High-Resolution (HRVIR) and 1 VEGETATION
	SPOT 5	2002	2 High Resolution Geometric (HRG), 1 High Resolution Stereoscopic (HRS) and 1 VEGETATION
LANDSAT	LANDSAT 1 LANDSAT 2	1972 1975	Multispectral Scanner System (MSS)
	LANDSAT 3	1978	Multispectral Scanner System (MSS) with additional thermal band
	LANDSAT 4 LANDSAT 5	1982 1984	Multispectral Scanner System (MSS) and Thematic Mapper (TM)
	LANDSAT 6	1993	*unsuccessful to reach orbit
	LANDSAT 7	1999	Enhanced Thematic Mapper Plus (ETM+)
	LANDSAT 8	2013	Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Table-2. Characteristics of the satellite imagery's sensor.

Sensor	Band	Spatial Resolution	Temporal Coverage
MSS	4 bands	0.068 km 0.083 km	2 weeks and 4 days
TM	7 bands	0.030 km, 0.120 km (TH)	2 weeks and 2 days
ETM+	8 bands	0.030 km, 0.060 km (TH), 0.015 km (pan)	2 weeks and 2 days
OLI & TIRS	11 bands	0.030 km, 0.100 km (TH), 0.015 km (pan)	2 weeks and 2 days
HRV	4 bands	0.020 km (multi), 0.010 km (mono)	4-5 days revisit
HRVIR	5 bands	0.020 km (multi), 0.010 km (mono)	4-5 days revisit
VEGETATION	4 bands	1 km	1 day
HRG	5 bands	0.010 km (VIS + Near-IR), 0.020 km (SWIR), 0.005 km or 0.0025 km (pan)	4-5days revisit
HRS	1 band	0.010 km	3 weeks and 5 days

*TH = thermal band
*pan = panchromatic band
*multi = multispectral band
*mono = monospectral band

Quickbird-2 was launched in October 2001 and since then has supplied the majority of satellite and aerial imageries. It consists of two bands, which are (1) panchromatic band with 0.65 meter resolution with revisit period of 2.5 days and (2) multispectral band with 2.62 meter resolution with revisit period of 5.6 days. While, IKONOS which was launched in September 1999 offers panchromatic image at spatial resolution below 0.001 kilometer. While, it offers multispectral bands of 0.0032 kilometer at nadir and 0.004 kilometer at 26 degrees off nadir. The revisit period for IKONOS is roughly 3 days.

SHORELINE DETECTION

Remote sensing have become useful tool to detect the changing on the surface of earth by using the satellite images. A various applications of remote sensing have used to spot the changing of land use and the changing of covering land (Alqurashi & Kumar, 2013). So, this section will discusses on the recent shoreline detection techniques that have been applied in remote sensing application.

Pixel swapping algorithm

Pixel-swapping (PS) algorithm in remote sensing is intended to transform the pixels of land cover into sub-pixel of land cover class that has been obtained by soft classifier application based on remotely sensed image and initialized every pixel into sub-pixel hard classes (Shen, Qi, & Wang, 2009). The sub-pixel level depends primarily on the zoom factor (z) (Su, Foody, Member, Muad, & Cheng, 2012). As for example, if the zoom factor is equal to 5, the total number of sub-pixel-level for each pixel is 25. The sub-pixels in each pixel are arranged randomly. The location of sub-pixels will be jumbled while the amount of sub-pixels inside a pixel and its class proportion remain the same (Shen *et al.* 2009), (Atkinson, 2005).

Generally, there are three basic steps to reorder the sub-pixels localization as proposed by Atkinson (Atkinson, 2005). Firstly, the attractiveness, A_i of a sub-pixel i is forecasted as a distance-weighted function, where $j \in \{1,2,\ldots,j\}= 1, 2, \ldots$, is the neighbourhood pixels:

$$A_i = \sum_{j=1}^{J} \lambda_{ij} z(x_i) \tag{1}$$

where, $z(x_i)$ is the binary class of the j^{th} pixel at location x_j, and λ_{ij} is a distance-dependent weight based on:

$$\lambda_{ij} = \exp\left(\frac{-h_{ij}}{a}\right) \tag{2}$$

where, h_{ij} is the interval between the sub-pixel x_i, which the attractiveness will be computed and the neighbouring sub-pixel x_j. While, a is the non-linear parameter of the exponential model.

Secondly, according to the attractiveness between each of the sub-pixels within a pixel, the algorithm produces the outcome on a pixel-by-pixel basis. In each of a pixel, the least attractive position at which the sub-pixel

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is presently assigned to "1" is represented as A, while the most attractive position at which the sub-pixel is presently assigned to a "0" is represented as B:

$$\mathrm{A} = (x_i : A_i = \min(\mathrm{A}) \mid \upsilon(x_i) = 1) \tag{3}$$

$$\mathrm{B} = (x_j : A_j = \min(\mathrm{A}) \mid \upsilon(x_j) = 0) \tag{4}$$

For the third step, two sub-pixels within a pixel will be swapped between candidate A and candidate B if candidate A is less then candidate B or otherwise, no change is made. These three steps are iterated until a certain number of iterations or when the pixel positions remain the same.

Some modifications have been done to reduce the computational time for the iteration of sub-pixel mapping in original PS algorithm. Firstly, Shen *et al.* (2009) introduced a technique using spatial attraction model in the process of initializing of sub-pixel (Shen *et al.* 2009). Function of the spatial attraction model is straightly approximate the class of the sub-pixel referring to the proportion of the class of its neighboring pixels. Secondly, Su *et al.* (2012) introduced a method to combine methods of contouring and PS to improve super-resolution analysis (Su *et al.* 2012). The approach of contouring is to fit a 0.5 class membership in the soft classification to split between two classes which are an aim object and its background. Contour based PS (CPS) is divided into two approach: (i) CPS1 is a variation based on normalized attractiveness from the basic of PS algorithm (ii) CPS2 is one step adding into the basic of PS algorithm to make the output soften.

Active contour

Active contour model or also known as snake model was first introduced by Kass, Witkin and Terzopoulos in 1987 (Kass, Witkin, & Terzopoulos, 1988). Basically, active contour is used to segment the shoreline by utilizing the shape outline, so that the energy functional is minimized to obtain the required segmentation (Lankton, Member, & Tannenbaum, 2008). There are several issues raised because of the snake model, especially initialization and low convergence to the boundaries of image curve (Lankton *et al.* 2008).

Caselles *et al.* (1997) then introduced Geodesic or Geometric Active Contour (GAC) to overcome the problem of snake model by using the level set method, which is more versatility (Lankton, 2009) (Caselles & Kimmel, 1997). The ability of GAC compared to snake model is the ability to handle the topological changes of the image contour. GAC can be separated into two categories: edge-based method and region-based method (Tian, Zhou, Wu, & Wang, 2009). Edge-based method utilizes image gradient to recognize the object borders. Meanwhile, region-based method finds the boundaries by searching exhaustively on every areas of interest based on definite region descriptor. It was introduced by Chan and Vese and known as Chan-Vese model (Chan & Vese, 2001). Its performance is better than edge-based method for an image that contained weak object boundaries without relying on image gradient. However, Chan-Vese model is not efficient and it is hard to initialize between level set function to the signed function (Tian *et al.* 2009).

Yun *et al.* (2009) have proposed a method by using global energy and its variations based on an internal energy to overcome the problem of Chan-Vese model and RSF model which are sensitive to noise (Tian *et al.* 2009).

Artificial neural network (ANN)

Artificial Intelligence (AI) is a technique that usually used to classify the extracted features into the desired class, which in this case as sea or land (Berberoglu, Lloyd, Atkinson, & Curran, 2000). The development of ANN method was inspired by human brain recognition mechanism that has been applied in many applications. In pattern recognition, there are six commonly used ANN models; (1) Kohonen's self-organising feature maps; (2) multi-layer perceptron; (3) Carpenter classifier; (4) Hopfield network; (5) single-layer perceptron; and (6) Hamming networks.

In remote sensing application, the commonly used ANN model is feed forward network which are multi-layer perceptron (MLP), probabilistic neural network (PNN), radial basis function (RBF), and generalised regression neural networks (GRNN) (Foody, 2006). An early model as proposed by Rumelhart *et al.* (1986), is the basis for MLP (Berberoglu *et al.* 2000). This model generally have three or more interconnected layers or nodes where the first layer acts as an input while the last layer acts as the output. While, the hidden layers are the layers between the input and output layers. The interrelation among the nodes has a weighted link that will be summed to produce the output value of its weighted inputs.

Weight of the input of one node is determined as stated by:

$$\mathrm{net}_j = \sum \omega_{ji} o_i \tag{5}$$

where, ω_{ji} stands as the weight between two nodes of node i and node j, and o_i is the result from node i. Based on the equation below, the result for node j is calculated as:

$$o_j = f(\mathrm{net}_j) \tag{6}$$

where, the function f is generally a non-linear sigmoid function that is the sum of the weighted inputs that have been used before the signal of the network going through the subsequent layers. Output from the network is produced when the processed signal reaches the output layer. The network error is concluded if there is dissimilarity between the accepted value for the output and the real network output. Then, the value of the error is back-propagated and the weights of the relation are transformed by following the universal delta rule.

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$$\Delta\omega_{ji}(n+1) = \eta(\delta_j o_i) + \alpha\Delta\omega_{ji}(n) \quad (7)$$

where, η stands for the estimation of learning parameter, δ_j is the indication level of the changing of the error, and α is the momentum parameter that the training process will stop when the sum of error in the network reduce to an early specified rank.

Generally, the ANN methodology can be considered as "winner takes all", where the assigned value of "1" represents the output node that will be activated, while others output nodes were set as low.

For RBF model, it is slightly different from MLP model, where it contains a single layer of hidden intermediate layer. Based on Bishop (1995), the hidden layer function is based on radial basis transformation by using Gaussian function as kernel. Center location and its width are extracted for every radial basis function. Similar to MLP model, the output layer of RBF model applied the linear summation function. The training network of RBF model consists of 2 stages: (1) unsupervised analysis to determine the weight between the input and the hidden layers (2) determination of the weight between hidden and output layers based on linear supervised method (Bishop, 1995).

While, PNN model used mainly to classify a bigger network compared to MLP and RBF model (Foody, 2006). The derivation of classification probability density functions (PDF) used to classify the class of membership for all cases (Specht, 1990).

Then, GRNN model has the similarities with PNN but it has four layer where it has a radial basis layer and a special linear layer known as regression layer to solve problems of regression only. There are two types of unit obtained from regression layer, the calculation of regression outputs and the probability of density. GRNN constructed same the problems as PNN that needed a larger process for its application and influenced its computation time to use on larger size of data sets.

DISCUSSION

This section discusses on advantages and limitations of using the method described in the previous section.

Pixel swapping algorithm

As proposed in section of shoreline detection techniques, the PS algorithm is a very straight forward method that performs sub-pixel mapping that class the satellite image into several groups. However in certain conditions, this method cannot perform accurately (Atkinson, 2005). Firstly, PS created input image which is a traditional set where the boundaries are precisely clarified. If the boundaries are vague, method of soft classification was found to be more appropriate since the noise will result in inaccurate shoreline. Secondly, the maximization of spatial correlation among neighbouring sub-pixels has a tendency to produce compact convex shapes. Thirdly, image with height resolution such as satellite imagery requires a lot of iteration and time.

The method in (Shen *et al.* 2009) used spatial attractiveness model to improve the random initialization of PS. The results show that their method is more accurate on sub-pixel mapping compare to basic PS. It is also less sensitive to zoom factor. Even though, computational time increased during initialization compared to random initialization but the iteration time is reduced for bid size of images.

Lastly, (Su *et al.* 2012) compared several methods that include basic PS, contouring and CHNN. The results showed CPS1 and CPS2 return the best accuracy with low Root Mean Aquare Error (RMSE) and Mean Absolute Error (MAE) calculation. By using satellite image, both CPS are capable to detect the shape of building superiorly compared to contouring and CHNN methods. But, the neighbouring ratio plays an important part in PS-based method. It can influence the boundaries detection as the neighbouring ratio increases where both CPS failed to perform well. Additionally, CPS1 performs better in detecting rounded object compared to CPS2.

Active contour

Snake model is mostly useful to detect edge and line features. The main advantage of active contour compared to typical image segmentation methods is better accuracy of sub-pixels on the boundaries. However, some limitations of the snake model (Tian *et al.* 2009) are: (1) the initial contour line must close enough to the target image, (2) optimal number of control points must be carefully selected as it will influence the behaviour of snake model, (3) it is suitable only for drawing out single-object contour where concave shape is found to be incompatible.

The level set method is easy to implement and tolerate at very difficult curve behavior. But the drawback of this method is high computational burden. Whitaker has proposed a method to overcome this problem by introducing spare field method (SFM) that uses a list of points to locate zero level set and also for the points adjacent to the zero level set (Lankton, 2009).

Based on paper (Tian *et al.* 2009), Table-3 summarized the advantages and limitations of edge-based and region-based methods.

Table-3. Advantages and limitations of edge-based and region-based methods.

	Advantages	Limitations
Edge-based	- no limit on global used in the image - target objet and background can be heterogeneous	- high sensitivity to image that contain noise - depend on initial curve placement
Region-based	- Less sensitivity to image that contain noise - powerful in implementation of initial curve placement	- for segmentation of heterogeneous objects, the method not proper to use because it depended on global statistics

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Artificial neural network (ANN)

Tu (1996) has summarized the advantages and disadvantages of Artificial Neutral Network approach as shown in Table-4. ANN model is a non-linear model, which is easy to implement compared to complex statistical methods. However, ANN is a black box learning approach where it cannot recognize which one is the most important parameter (Tu, 1996).

Table-4. Advantages and disadvantages of artificial neural network approach.

Advantages	Disadvantages
▪ ANN development only needs a few formal statistical training ▪ can completely detect complicated non-linear relationship between independent and dependent variables ▪ have the ability to sense all possible relations between the predictor variables ▪ can be expended using multiple different training algorithm	▪ have restricted ability to clearly classify the possible fundamental relationships ▪ more tricky to use ▪ needs larger computational resources ▪ It is less robust to overfitting ▪ neural network models progress is still under research and has a lot of methodological issues before accurate applications

CONCLUSIONS

In conclusion, among the discussed methods, pixel swapping is found to have the best trade off between accuracy and computational burden. It is also to code but depends heavily on sub-pixel size. However, the impact of high computational burden can be lessened by using parallel programming via NVIDIA Cuda. Besides, Su *et al.* (Su *et al.* 2012) have also proposed a method by combining both contouring and pixel swapping algorithm if the computational burden is not a concern. As for future work, we would like to propose multiple models approach (Zulkifley & Moran, 2012) in classifying the shoreline, especially for vague images.

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