HOPFIELD NEURAL NETWORK AND QUASI-LINEAR TRANSFORM MODEL FOR SIMULATION LONGSHORE CURRENT PATTERN FROM RADARSAT

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Abstract

This study introduced a new approach for modeling longshore current pattern from sequential RADARSAT SAR images. Doppler frequency gradient shift from the two sequential RADARSAT images has been estimated. This model utilized to simulate the longshore current pattern. The quasi-linear model used to map the longshore pattern detected by Doppler frequency shift into the real longshore current simulated from significant wave height at breaking zone. A Hopfield neural network was applied to compare between longshore current estimated from Doppler frequency gradient shift and ones modeled from quasi-linear .

The result shows that the neural network method has a high degree of accuracy with 78.54% for modeling longshore surface current in area of high backscatter variations. The longshore current direction can detect easy by neural network method compared to quasi-linear model. In conclusion, neural network method could be used as an automatic method for detecting longshore current pattern. Neural network can detect the longeshore current along the azimuth direction or range direction.

Keywords: Neural network-Doppler frequency model and Longshore current pattern

1.0 Introduction

Longshore current patterns play significant role in sediment distributions along the coastline (Komar 1976). Sediment distributions a long the coastline are indicator for shoreline change (Maged 2001). Longshore current considers as a movement of water parallel to the shore, caused by oblique incident swell (Komar, 1976). This means that the onshore swell movements can be utilized for longshore current simulations. The classic method for study longshore current are based on the rider wave buoy. Scientists tend to simulate longshore current from the record of rider wave buoy were anchored onshore or offshore. Scientists and researchers also used a current meter to detect the speed and direction of longshore current. These classical methods require much efforts and time. SAR data assimilation in real time could be a major tool for longshore current modeling and forecast. These wave spectra used to simulate the longshore pattern. Maged (2001) proposed a method based on the direct quasi-linear transform to predict shoreline change. This model was based on the simulation of longshore current from the significant wave height at breaker zone. Other studies estimated the surface current velocities from sequential satellite image was based on Maximum Cross-Correlation. Maged (2000) and Maged and Genederen (2000) have estimated a surface current vectors from single RADARSAT data by utilizing a Doppler frequency shift model. They found that simulated current velocities from RADARSAT data are agreed with surface current predicted from tidal table.

In this paper, a Hopfield neural network is utilized to model longshore current from sequences of SAR images. This study focused on the following approaches; (i) Quasi-linear transform can be used to simulate longshore current pattern (ii) Doppler frequency shift model can be used to detect the gradient change of sequences SAR backscatter images (iii) A Hopfield neural network can be appropriate method for development of automatic and reliable operational systems for the measurement of longshore current velocities and directions from sequential SAR images. The main objective of this study was to exam a Hopfield neural network for detecting longshore current pattern.

2.0 Methodology

The method consists on three sub-models: quasi-linear model used to simulate longshore current from a significant wave height, Doppler Frequency shift sub-model to detect the longshore current from SAR image intensity gradients, and the two modeled are matched with the a Hopfield neural network.

2.1 Quasi-linear Model for Longshore Current Simulation

This model was applied from the study of Maged (2001). As the longshore current are function of significant wave height H_s detected from azimuth cut-off l model as follows:

$$U = F(l, H_s) \qquad (1.0)$$

2.2 Doppler Frequency Model for Longshore Current

The quasi-linear transfer model can be used to map the tidal current pattern from RADARSAT SAR image into a real current ocean. This is because e of the fact the water movement pattern either wave spectra or current pattern always imagine in azimuth direction due to the effect of Doppler frequency shift. The current-RADARSAT (V) quasi transform may be expressed as

$$V_{cx,cy} = m\{U(v_{cx}, v_{cy}); G(U_{x,y})\} \qquad (2.0)$$

where $U(v_{cx}, v_{cy})$ is the tidal current components in the azimuth and range directions. m represents the linear operator which is the current-RADARSAT transform. *G* represents parameters of the current-RADARSAT map which readily based on geophysical conditions of current pattern movements (i.e. velocities and direction) and RADARSAT properties such as Doppler frequency shift.

The azimuth velocity component v_{cx} of surface current was modeled by estimating its displacement vector. The Doppler spectrum of the range compressed RADARSAT raw data is modeled by performing a Fast Fourier transform (FFT) in azimuth direction. The current velocity for each pixel is divided into azimuth and range velocity. The azimuth velocity component of current movement is obtained by using a block-matching algorithm. The block-matching algorithm was performed to determine the best match between blocks in two successive windows. The difference of the positions in two windows is considered as the displacement vector (Martian, 1997). Then, the azimuth component can be determined from the displacement vector Dx. It can be given by

$$v_{Cx} = v_{Ax}\left[1 - \left(1 - \frac{2\Delta x dx v_{Ax}}{\Delta f_i R_T l}\right)^{-0.5}\right] \qquad (2.1)$$

where dx is the pixel spacing in the azimuth direction, v_{Ax} is the platform velocity, v_x *and* l denote the carrier wavelength and antenna speed in azimuth direction *x*, f_i are the look center frequency which estimated from Fourier Transform, and R_T is the slant range. The current speed in the range direction has a different form. This is because of the fact that the change of current velocity in range direction is erroneous. This is because of the range migration correction. In the Doppler spectrum, the range current velocity v_{Cy} is given by

$$v_{Cy} = -\frac{l f_{D_T}}{2\sin g} \qquad (2.2)$$

where g is the incidence angle and f_{D_T} is Doppler shift frequency. The current speed direction can be given by

$$q = \tan^{-1}\frac{v_{Cy}}{v_{Cx}} \quad (2.3)$$

2.3 Neural Network Model

In matching process using the Hopfield neural network, identified features have to be mathematically compared to each other in order to build an enrgy function that will be minimized. Let $a \in \{-1,1\}^{Z_n}$ be image used to represent neuron state. Initialize a with known longshore image pattern. The weights of the sysnaptic connections $T \in (R^{Z_N})^{Z_N}$ that controls the intensity of longshore current in both quasi-linear and Doppler frequency shift models link between the output e_i of neuron i to neuron j which is defined by

$$T_i(j) = \left\{\sum_{k=1}^{K} e_j^k e_i^k\right\} \quad \text{if } i \neq j \quad (3.0)$$

$$T_i = \{0\} \quad \text{if } i=j \quad (3.1)$$

Let the output of neuron j defined by

$$e_j = 0.5(1+\tanh\ p_{0,j}) \quad (3.2)$$

where $p_j = \sum_{i=1}^{K} T_{i,j} e_j$ **.** The energy of network can be given by

$$E = -0.5\sum_{i=1}^{k}\sum_{j=1}^{k} T_{i,j} e_j^K e_i^k \quad (4.0)$$

The movement pattern of a neuron along the azimuth direction can be given by

$$de = \int_0^t E dt \quad (5.0)$$

The Hopfield network is utilized to detect the similar pattern being translated by the energy function. Energy function represents the similarity between features and vectors close to each other i.e., have same length and direction which means smoothness (Emery et al., 1992). The Euler method could be used to minimized the energy function of equation of neuron motion as follows

$$e_{ij}(t+\Delta t) = e_{ij}(t) + \Delta t\left(\frac{de_{ij}(t)}{dt}\right) \quad (6.0)$$

3.0 Result and Discussion

The longshore currents vectors simulated from Doppler frequency shift and quasi transform model are shown different in lengths and directions. The longshore current vectors simulated from quasi linear model tend to move along the range direction. This could be due to the high ration of R/V which is higher in RADARSAT image. This induces wave motion a long the azimuth direction due to high effect of velocity bunching (Maged 2001). If the incident wave propagated along the azimuth direction, will be induced the longshore current moved perpendicular to azimuth direction i.e. range direction. In Doppler frequency Shift model, the longshore vectors shifted by oblique angle between azimuth and range direction. The maximum velocities of longshore currents were modeled from Doppler frequency shift model was 1.2 m/s while ones modeled from quasi-linear model were 1.7 m/s (Figures 1 and 2). Figure 3 shows the vector currents movements derived from Hopfield neural network. The vectors seems to be coherent locally. Along the energy backscatter gradient the clearly longshore current flow was occurred. The velocities were modeled from Hopfield neural network was approximately similar with Doppler frequency shift model results. The maximum longshore current velocity derived from Hopfield neural network was 1.25 m/s. However, there was differences in the vectors propagation as the alongshore current vectors tend to move away from azimuth direction by 30° and range directions by 10°. This is because of the fact that neural network method is more local method, trying to establish a match between pattern of both quasi-linear and Doppler shift frequency model. Comparisons between the three vectors shown that they were spatially varying in length , while those of the Doppler frequency shift model are quite uniform. Longshore current simulation from quasi-linear wave spectra alone did no provide spatial distribution of vectors over energy variation along the azimuth or range directions (Figure 1). This is because of the fact that, vectors were generated from significant wave height that derived from azimuth cut-off model. The azimuth cut-off model could not be able to capture the fully change of intensity spectra away from the shoreline by 400 m. This is because that the azimuth cut-off model estimated from window spectra size of 512x 512 pixels and line which cover area with large scale of 46 km x 46b km. The low spatial resolution of azimuth cut-off model did not allow to detect the change of longshore current movements energy with distance of 400 m. In contrast, Doppler frequency shift was applied to change of intensity frequencies with individual pixels. This was allowed to capture the spatial distribution of vectors over the gradient change of spectra intensity away from the shoreline with 400 m. Displacement vectors generated by the neural network can be noticed along the sharp intensity gradients. Moreover, the neural network could be able to detect the longshore current vectors along the azimuth and range direction. According to Emery et al., (1993) Hopfield network is best suited for binary image classification. Patterns were described as vectors. These information are absent in the original data. The neural network able to identify the propagation direction of any patterns. This could be the reason why the surface current vectors have a direction. In addition the one of the common components of Hopfield network is the propagation rule. The propagation rule defines how surface current states and its synaptic strength combine as input to a neuron

4.0 Conclusion

It can be said that Hopfield neural network was able to map the longshore current propagation. Quasi-linear model was able to detect the longshore current along the range direction. The Doppler frequency shift was able to detect the longshore current propagation between azimuth and range direction. The Doppler frequency model and neural network agreed that the longshore current speed was approximately less than 1.3 m/s.

References

Emery, W.J.,m Fowler, C., and Clayson, C.A. 1992. Satellite-image-Derived Gulf Stream Currents Compared with Numerical Model results. J. Atm. Ocean Technology. 3: 286-304.

Komar, P.D . 1976. *Beach Processes and Sedimentation*. Prentic-Hall, New Jersey.

Maged, M. 2000. " Finite Element Simulation of Tidal Current Movements on Malacca Straits. Proceeding of IGARSS'2000. Honolulu, Hawaii 24-28 July 2000. Vol.II. pp:2966-2968.

Maged, M. and J. Genderen, 2001. Texture algorithms for oil Pollution Detection and Tidal Current Effects on Oil Spill Spreading. Asian J. Geoinformatics, 1, 33-44.

Maged M. 2001. A Comparison between Quasi-linear and Velocity Bunching Models for Modelling Shoreline change. Asian Journal of Geoinformatics. Vol (2) (3). pp:3-13.

Martain K. 1997. "Detection and Focused Imaging of Moving Objects Evaluating a sequence of Single Look SAR images". Proceedings of 3rd International Airborne Remote Sensing Conference and Exhibition, Copenhagen, Denmark, Vol. I, pp.393-400.

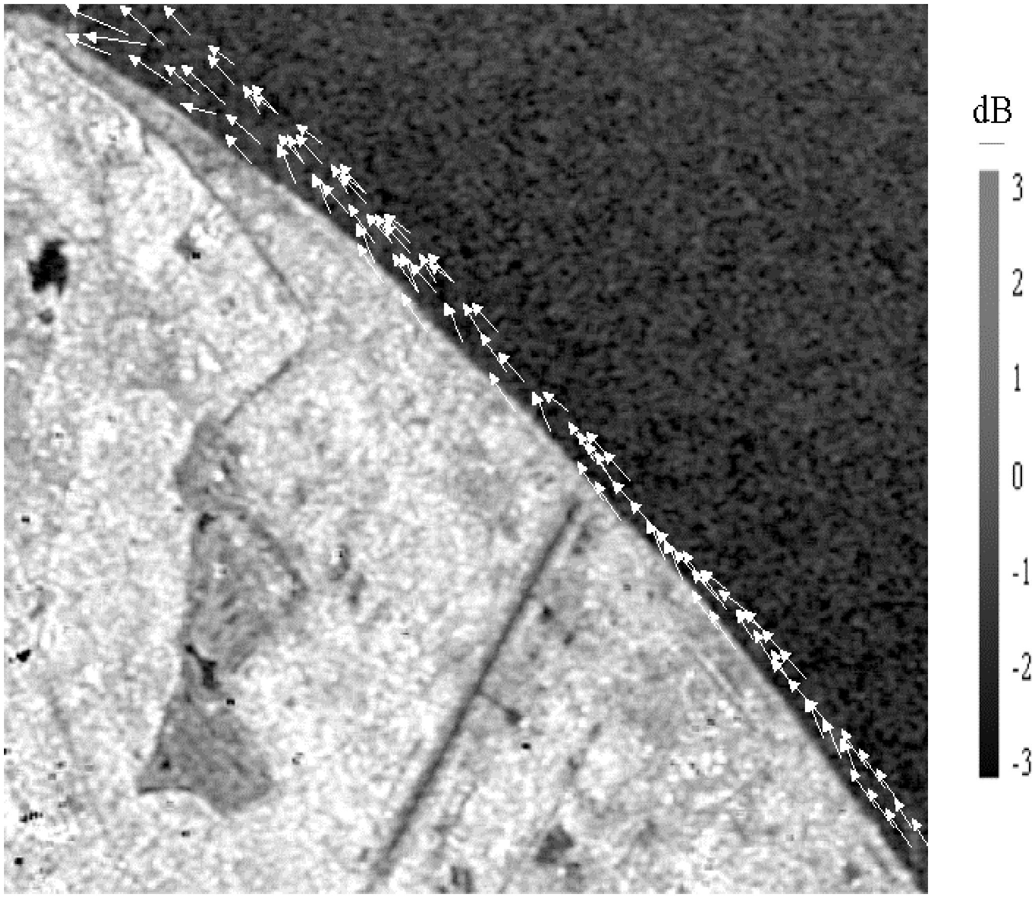

Figure 1 Longshore simulated from significant wave height estimated from quasi-linear Model

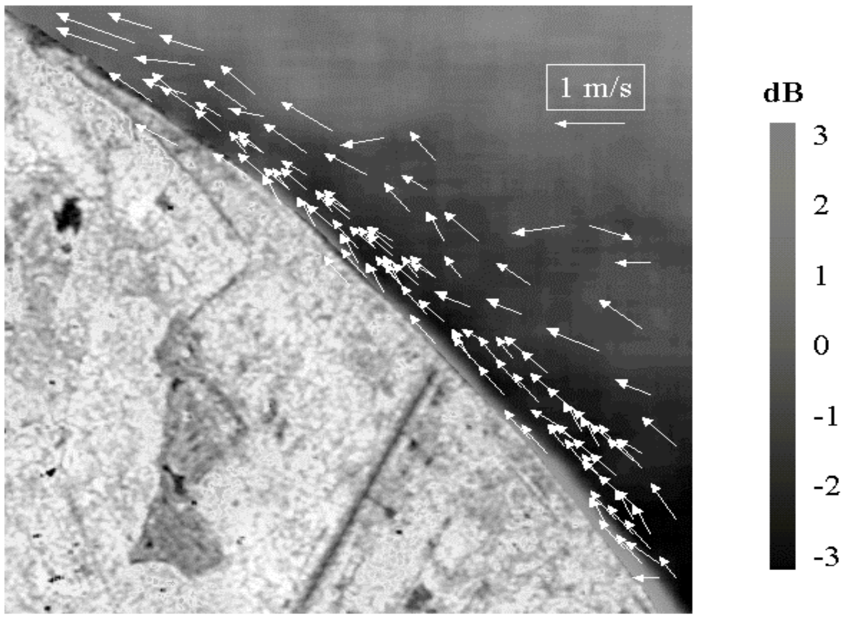

Figure 2. Longshore current simulated from Doppler frequency Shift Model

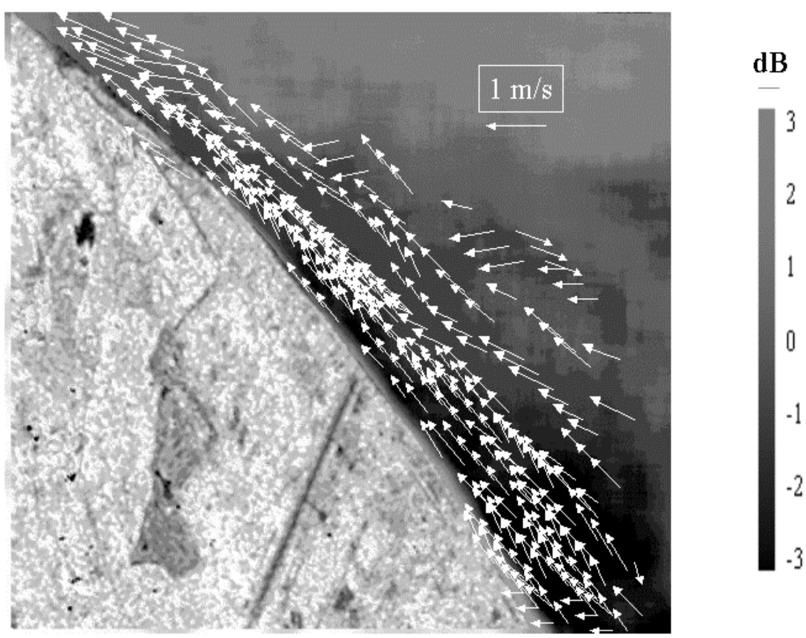

Figure 3. Longshore Current Simulated from Neural net work