UTILIZATION OF TIUNGSAT-1 DATA FOR MODELLING SEA SURFACE CURRENT

Maged Marghany, Mazlan Hashim and Arthur P. Cracknell
Department of Remote Sensing
Faculty of Geoinformation Science and Engineering
Universiti Teknologi Malaysia
81310 UTM, Skudai, Johore Bahru, Malaysia
Email: maged@fksg.utm.my,
magedupm@hotmail.com,
mazlan@fksg.utm.my,
cracknellarthur@hotmail.com

ABSTRACT

This study introduces a new approach for operational TiungSAT-1 data for modeling coastal current pattern. The Hopfield neural network was used to model sea surface current movements. In matching process using Hopfield neural network, identified features have to be mathematically compared to each other in order to build an energy function that will be minimized. In this context, the neuron network has been taken in two dimensions; raw and column in order to match between the similar feature of surface pattern, it was required that the two features were extracted from the same location. The Euler method is used to minimized the energy function of neuron equation. The study shows that the surface current pattern can be modeled by high accuracy of ±0.14 m/s.

1.INTRODUCTION

Developing countries have tremendous attentions to exploit the advance space technology for economic development. In this context, there are great opportunities in the area of research and development, derivative industries, commercial applications and professional services in related fields. Several developing countries such as China, India, Thailand, and Malaysia have moved towards space industry for non-commercial and non-military purposes. In fact, the space environmental observations might be provided appropriate solutions for economy problems and prefect commercial strategy planning. Furthermore, Space industry and technology in particular have proved excellent abilities for monitoring and solving several environmental problems, for instance, land mining, disasters, coastal zone management etc. Among development countries, Malaysia has been approached space industry by lunching the first microsatellite (TiungSAT-1) in 2000,that included several remote sensing instruments for environmental monitoring. in addition to commercial land and weather imaging TiungSAT-1 satellite payloads offers FM and FSK Amateur Radio communication. Nevertheless, few environmental studies have been implemented TiungSAT-1 satellite data in Malaysia. Researchers and scientists have been concluded that there are aplenty opportunities for utilizing such small satellite of TiungSAT-1 for environmental monitoring (Mazlan and Hazli 2001 and Alvin et al. 2003). MataJaferi et al. (2002) have utilized TiungSAT-1 satellite data in water quality mapping. However, this study did not show accurate results due to the absence of in situ measurements. Conversely, Mohd and Ming (2003) have stated that the TuingSAT satellite data are not useful in some of marine applications such as ocean color mapping due to the unavailability of the blue band and the stripping impacts in the TiungSAT-1 satellite data. By contrast, Mazlan and Hazli (2001) have implemented Fourier Transform to eliminate the stripping noise from TiungSAT-1 satellite data. In fact, Fourier Transform is useful image tool for spatial filtering and image regeneration through the application of an inverse Fourier Transform.

In this paper, we address the question of estimating sea surface current pattern using TiungSAT-1 satellite data. This is demonstrated using neural network technique. Hypotheses examined are (1) there are significant differences between the different bands in detecting ocean current feature patterns, (ii) Hopfield neural network can be applied to single data without needing to include sequential satellite data, (iii) Hopfield neural network can be used as procedures for eliminating inherent noises from TuingSAT-1 satellite data, and (iv) tidal has major impacts on current movements in such water body as the Malacca Straits.

2.METHODOLOGY

2.1 Data set

The TiungSAT-1 satellite data were acquired on 17 March 2001 over the coastline of Penang Island, Malaysia between 100° 09' E to 100° 16' E and 5° 18' N to 5° 26' N. TiungSAT-1 is originally a synchronous orbit at 90° inclination and altitude of 670 km where by the nominal orbital period can be taken as 98 minutes. Furthermore, TiungSAT-1 MSEIS satellite data is a multispectral data with Near Infra-Red (810-890 nm), Red(610-690 nm) and Green(510-590 nm) (Table 1) (Mazlan and Hazli, 2001).

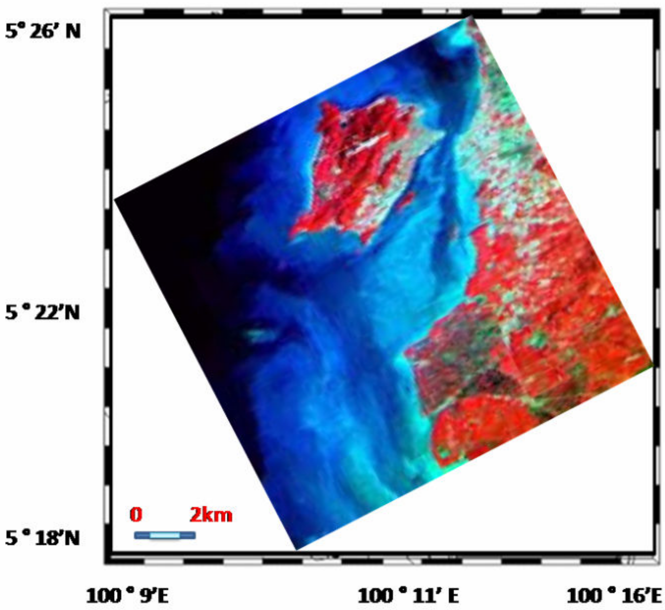

Figure 1. Study Area in Penang Coastal Waters.

Table 1. TiungSAT-1 Satellite Sensor Bands and Wavelengths

Band	Wavelength (nm)	Nominal spectral band
1	510-590	Green
2	610-690	Red
3	810-890	Near-infrared

2.2 Hopfield Neural Network

Neural network techniques are an artificial intelligence procedure that they belong to expert system and knowledge–based approaches to learning (Arik 2002 and Zhao, 2004). On the other hand, scientists have agreed that neural networks belong to the same classes of techniques as automated pattern recognitions, stereo vision, motion analysis, and object tracking problems (Côté and Tatnall 1995 and Cao and Wang 2003). In this context, scientists have defined a Hopfield model as a kind of neural network. The Hopfield network has no special input or output neurons but all are both input and output, and all are connected to all others in both directions (with equal weights in the two directions). Input is applied simultaneously to all neurons which then output to each other and the process continues until a stable state is reached, which represents the network output (Nasrabadi and Choo 1992; Côté and Tatnall 1997; Arik 2002; Zhao, 2004).

According to Côté and Tatnall (1997), Hopfield neural networks is considered as a promising method for determining a minimum of energy of function. For instance, motion analysis and object pattern recognitions might be coded into an energy function. Furthermore, the actual physical constraint, heuristics, or prior knowledge of objects and system can be coded into the energy function.

A pattern, in the context of the *N* node Hopfield neural network is an *N*-dimensional vectors $V = (v_1, v_2, ...v_n)$ and $U = (u_1, u_2, ...u_n)$ from space $S = \{-1,1\}^N$. A special subset of S is set of exemplar $E = \{e^k : 1 \le k \le K\}$, where, $e^k = (e^k{}_1, e^k{}_2, ..., e^k{}_n)$ and k is exemplar pattern where $1 \le k \le K$. The Hopfield net associates a vector from S with an exemplar pattern in *E.* In this context, the net partitions S into classes whose members are in same way of exemplar pattern that presents the classes. For sea surface current features in the TuingSAT-1 satellite image (f), let $f_t(i) \in \{-1,1\}$ to be represent neuron sates, i.e. either -1 or +1, which serve as processing units. Each neuron has a value at time t denotes by $f_t(i)$. The permanent memory of neural set was resided within the interconnections between its neurons which named by the strength of the synapse (w_{ij}) or connection between two pair of neuron $f(i)$ and $f(j)$, According to Nasrabadi and Choo (1992), the design specifications for this version of Hopfield net require that $w_{ij} = w_{ji}$ and $w_{ii} = 0$. Following, Zhang et al. (1999), the propagation rule τ_i which defines how neuron sates and weight combined as input to a neuron can be described by

$$\tau_i = \sum_{j=1}^{N} f_t(j) w_{ij} \qquad (1)$$

The Hopfield algorithm has consisted of (i) assign weights to synaptic connections, (ii) initialize the net with unknown pattern, (iii) iterate until convergence and continue features tracking. First step of assign weight w_{ij} to synaptic connection can be achieved as follows:

$$w_{ij} = \begin{cases} \sum_{k=1}^{K} e_i^{\,k} e_j^{\,k} & \text{if } i \neq j \\ 0 & i = j \end{cases} \qquad (2)$$

In second step, the pattern that is to be quantified is introduced to the net. If the vectors $V = (v_1, v_2, ...v_n)$ and $U = (u_1, u_2, ...u_n)$ are unknown patterns then, set

$$f_0(i) = v_i \qquad ,1 \le i \le N \qquad (3)$$

$$f_0(j) = uj \qquad ,1 \le j \le N \qquad (4)$$

Third step is involved the estimation of next sate values for the neuron in the set using the propagation rule and activation function *F*. This step can be expressed mathematically by given formula:

$$f_{t+1}(i) = F\left(\sum_{j=1}^{N} f_t(j) w_{ij}, f_t(i) \right) \qquad (5)$$

Repetition of second and third steps is involved as fourth step to perform quantification of another sea surface current pattern in TuingSAT-1 image.

Hopfield neural network could be identified current pattern features by mathematical comparing to each other in order to build an energy function. According to Côté and Tatnall (1995) the difference function to determine the discriminations between different features f_i, f_j by a given formula:

$$diff(f_i, f_j) = G.\max\left| \max(\frac{l_i}{l_j}, \frac{l_j}{l_i}) - L'', 0 \right| + H.\max[\min(\left|\theta_i - \theta_j\right|, 2\pi - \left|\theta_i - \theta_j\right| - \theta'', 0]$$

$$+ J.\max\left| dis_{ij} - dist'', \theta \right| \qquad (6)$$

where, L'' is curvature shape of current feature, dis_{ij} is the distance between sea surface current features f_i and f_j, and G and H and J are constants, and is an angle of orientation of local curve element θ. In addition, $dist''$ and θ'' are the minimum acceptable distance and the maximum acceptable rotation angle, respectively before energy function. In practice, the Hopfield neural network can be quantified by an Euler equation (Côté and Tatnall 1995) of motion which can be expressed as

$$\frac{dW_i}{dt} = \sum_{j}^{N} \tau_{ij}.(F\left(\sum_{j=1}^{N} f_t(j) w_{ij}, f_t(i)\right)\lambda_i W_i) + B = \frac{\partial E}{\partial f_{t+1}(i)} \tag{7}$$

where B is the external bias on neuron i, λ is the steepness of the function and E is the network energy (Wang et al. 1993; Juang 1999; Arik 2002) which can be defined as

$$E(V,U) = -0.5(v_1, v_2 ...., v_n) \begin{pmatrix} w_{11} w_{12} ....w_{1k} \\ w_{21} w_{22} ....w_{2k} \\ . \\ . \\ w_{n1} w_{n2} ....w_{nk} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ : \\ : \\ u_k \end{pmatrix} \tag{8}$$

Following Côté and Tatnall (1997). , the minimization of energy equation 8 can be used for sea surface current features tracking and stereo matching. The contribution of this study is to determine the current velocity in single TuigSAT-1 image. Sequences of point-like current features are selected as candidates for sea surface current movements in TiungSAT-1 image. The adjoining pixels of current features have to full the following criteria: (i) the mean energy of the current pixels must be higher than the mean energy of the surrounding pixels , and (ii) the number of sea current pixels should to be lied between a lower and upper bound. Finally, Hopfield algorithm is implemented on detected features, a displacement vectors, then is estimated by determining the center position of sequences of frames generated over candidate current feature (Figure 2).

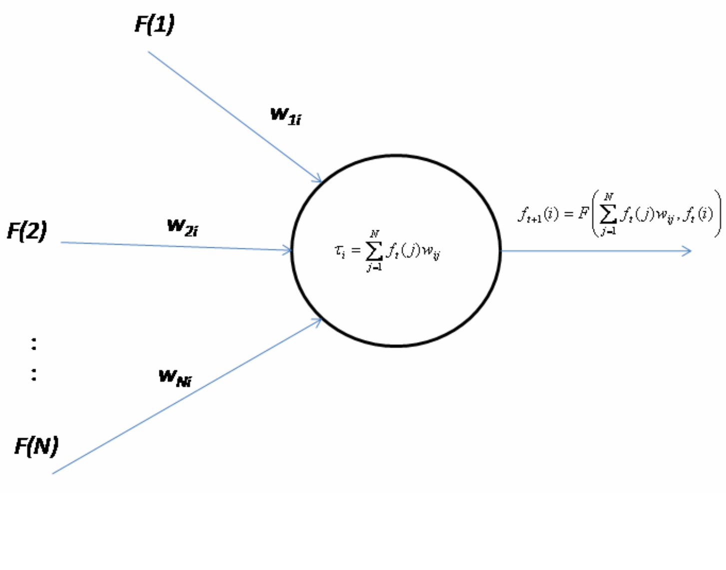

Figure 2. Hopfield Neural Network Used in this Study.

3.RESULTS AND DISCUSSION

Figure 3 shows the signature of the sea surface current feature whereby it is a obvious more in near-infrared with maximum gray value of 200 compared to other bands. Meanwhile, green band shows also higher gray level value of 180 along the current feature compared to red band. In fact, the water shallow and dominated by high concentration of sediment flow which provides high reflectance in green and near-infrared bands. Conversely, red band shows poor ability for sea current features detection due to its rapid spectra absorption (Robinson 1994). Strong current flow from several rivers are located along Penang coastline may be provide an explanation for strong of water plume appears in Figure 3.

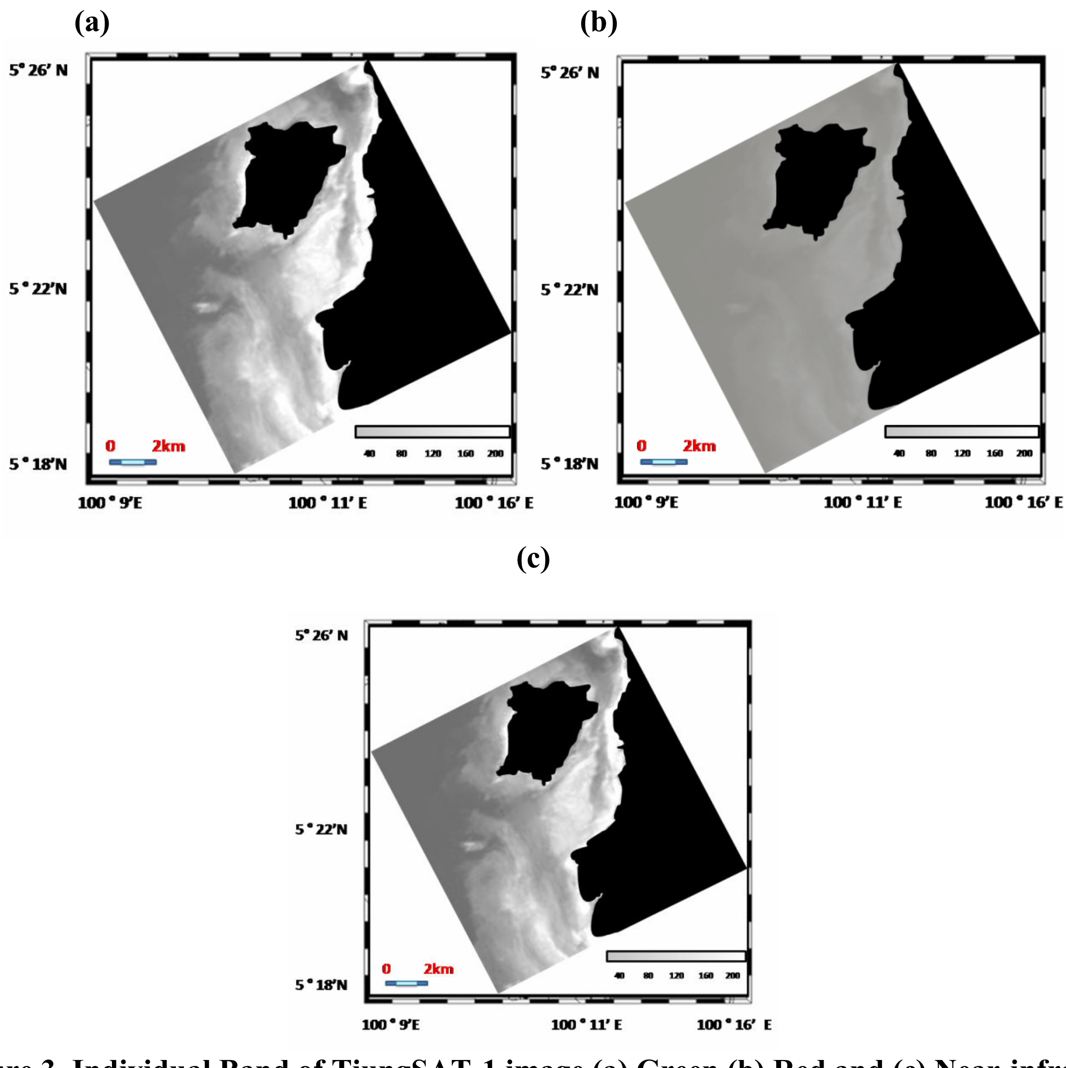

Figure 3. Individual Band of TiungSAT-1 image (a) Green,(b) Red and (c) Near-infrared

Figure 4 shows the results of Hopfield neural network for water plume feature in TiungSAT-1 image. It is interesting to find that the Hopfield algorithm provides a details of water plume structure morphology. This result is agreed with Côté and Tatnall (1997). Figure 5 shows the vector displacement which are appears closed to each other in green band compared to thermal band. Nevertheless, the Hopfield algorithm was tasted in green band and near-infrared band shows that the water vector flows are rotated around Penang island. In fact, Penang Island might be spilt the water flow from Malacca Straits to move parallel to Penang main land coastline and in westward direction along Penang Island. The current flow vectors are produced without noise. In fact, in homogenous flow such as water plume, the pixels are connected continuously which generated neighbor vectors are similar. In this context, the correlation peak corresponds to the true water flow displacement because the best matches between current vectors due to their local similarity. It is also can be noticed that Hopfield algorithms shows current vectors variations. Figure 5 depicts the similarity of vector displacement in both bands. In fact, the blur band is translated into its pattern representation and introduced to Hopfield net $f_t(i)$ is set equal to v_i , $,(1 \leq i \leq N)$. The input pattern was evolved through neuron state changes into the pattern $\hat{V} = (\hat{v}_1, \hat{v}_2, ..., \hat{v}_n)$ of the neuron states at convergence. Furthermore, exemplar pattern was represented the uncorrupted image. This was contributed due to the change of net to an exemplar pattern. This confirms the study of Liang and Wang (2000). The maximum current flow vectors is 0.6 m/s during its rotation around the island. The vectors within 0.24 m/s are appeared to move towards the island and it might be represented the water flow from the south of Malacca Straits. According to Maged and Mazlan (2005) the dominant water flow in Malacca Straits in one direction towards the northward. Moreover, it obvious that low current velocity ranged between 0.2 to 0.6 m/s is due to the impact of low tide. This is clear in image due to existence of high sediment accumulations during the acquisition time of the TuingSAT-1 data.

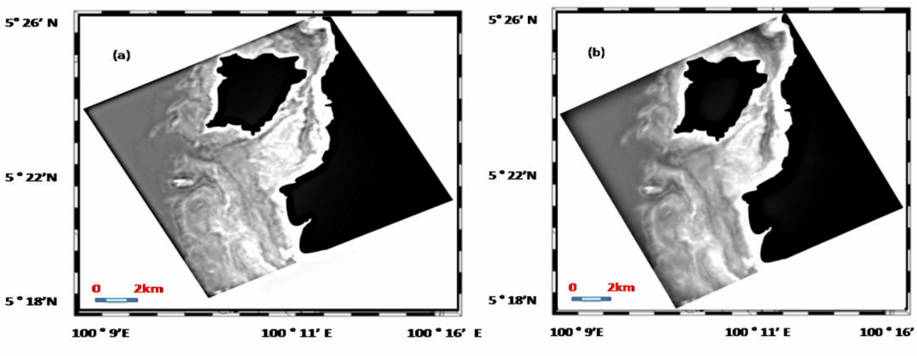

Figure 5. Output Results of Hopfield Algorithm for (a) Green Band and (b) Near-infrared Band.

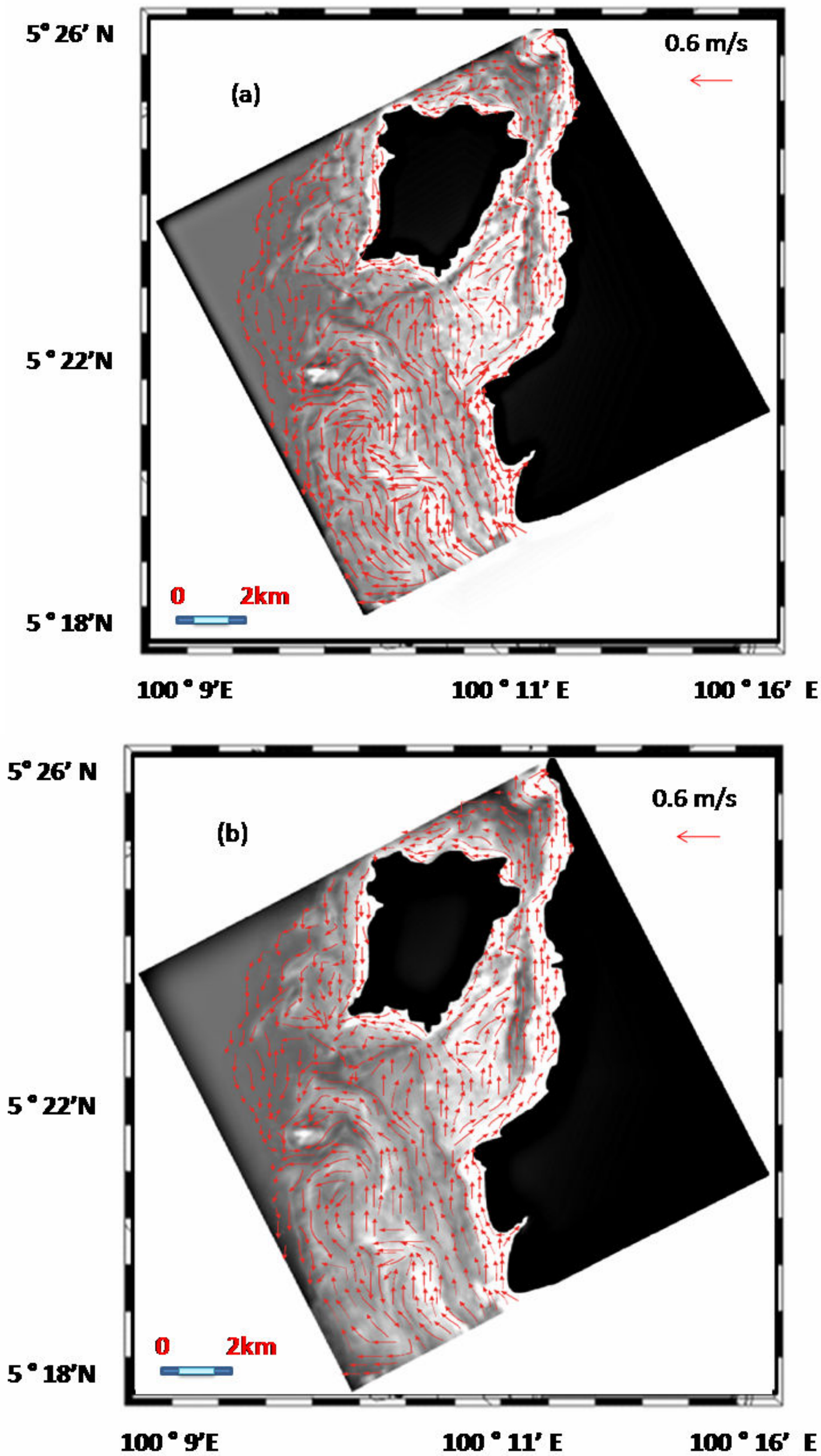

Figure 5. Vector Displacements Simulated by Hopfield Neural Network Algorithm for (a) Green band and (b) Near-infrared Band.

Figure 6 shows the regression relationship between the sea surface current modeled by Hopfield neural network and one estimated from tidal information. The scatter points are more close to the regression line with r^2 value of 0.989 and accuracy (root mean square) of ±0.14 m/s. This confirms that Hopfield neural network provides excellent information on coastal current movements. In fact, Hopfield algorithm parameters is function on the feature size and grey level gradient which could ensure accurate network convergence behavior.

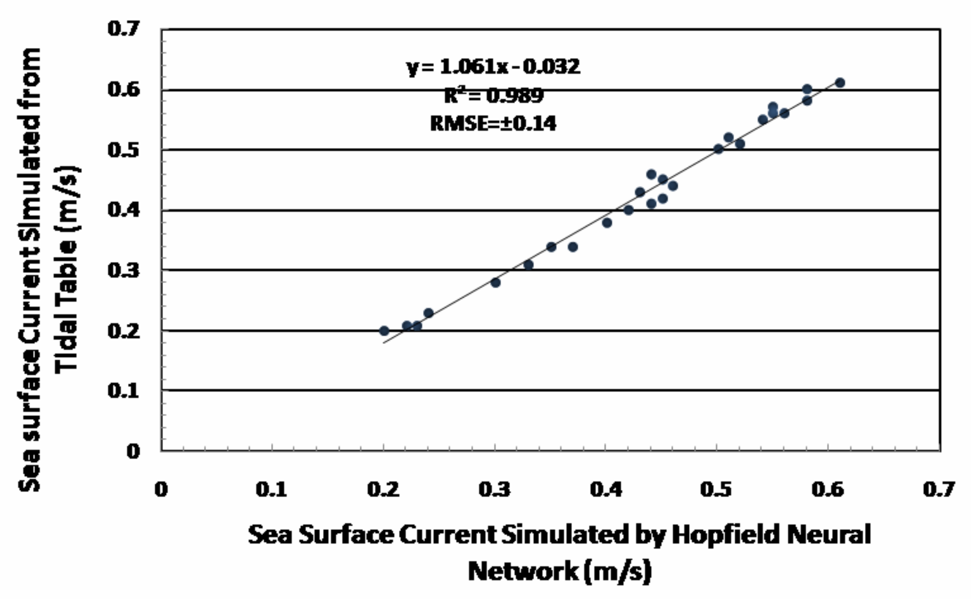

Figure 6. Regression Model for Simulated Sea Surface Current from Hopfield Neural Network and Tidal table.

4.0 CONCLOUSIONS

This work has demonstrated a new technique for estimating sea surface current from microsatellite data such as TiungSAT-1. The new technique is based on the modification of the Hopfield neural network parameters especially the way of estimation energy function. The cross correlation method is used to estimate the vector displacements of current features in several frames after applying Hopfield algorithm. It is shown that blur image is corrected by utilizing Hopfield neural network. The study confirms that Hopfield is capable algorithm to estimate the sea surface current velocity from green band and near-infrared band with high accuracy of ±0.14 m/s. It can be concluded that Hopfield neural network algorithm could be an excellent tool for image reconstruction and sea surface current modeling in single data.

Acknowledgements

We would like to express our appreciation to Universiti Teknologi Malaysia Research Management Center (RMC) for a great cooperation. In fact, RMC is providing excellent advice, plans and management for UTM researchers. We also acknowledge the financial e-science grants have received from the Malaysian Ministry of Science and Technology via its Intensified Research for Priority Areas programme.

References

Alvin, L., Meng, S., and Mazlan,H., (2003) Classification of TiungSAT-1 MSEIS Data for Land Cover Mapping with Hyperspectral Analysis Approach. In: TiungSAT-1: Data Applications. Astronautic Technology (M) Sdn. Bhd., Bukit Jalil, Kuala Lumpur, pp. 50-60. ISBN 983-41363-0-7.

Arik, S., (2002). A note on the global stability of dynamical neural networks, *IEEE Trans. Circuits Systems—I: Fund. Theory Appl.* **49**, pp. 502–504.

Cao J., and Wang,J., (2003). Global asymptotic stability of a general class of recurrent neural networks with time-varying delays, *IEEE Trans. Circuits Systems—I: Fund. Theory Appl.* **50** (1), pp. 34–44.

Côté, S. and Tatnall, A.R.L. (1997). The Hopfield neural network as a tool for feature tracking and recognition from satellite sensor images. *International Journal of Remote Sensing*. 18,4:871-885.

Juang, J.C. (1999). Stability analysis of Hopfield-type neural networks, *IEEE Trans. Neural Networks* **10** (6), pp. 1365–1373.

Liang, X.B. and Wang,J., (2000). Absolute exponential stability of neural networks with a general class of activation functions, *IEEE Trans. Circuits Systems—I: Fund. Theory Appl.* **47** (8), pp. 1258–1263.

Maged, M., and Mazlan, H., (2005). Simulation of Oil Slick Trajectory Movements from the RADARSAT-1 SAR. Asian Journal of Geoinformatics, Vol.5, (4). pp:17-27.

Mazlan, H., and Hazli, H., (2001). Radiometric and geometric information content of TiungSAT-1 MSEIS Data. In: TiungSAT-1: From Inception to Inauguration. Astronautic Technology (M) Sdn. Bhd., Bukit Jalil, Kuala Lumpur, pp. 185-200. ISBN 983-867-193-2.

Mohd, I. S. and Ming, L.C., (2003). Assessment of the Capability of TiungSAT-1 Satellite Data for Mapping Chlorophyll Distribution. In: TiungSAT-1: Data Applications. Astronautic Technology (M) Sdn. Bhd., Bukit Jalil, Kuala Lumpur, pp. 44-49. ISBN 983-41363-0-7.

MatJafri, M. Z. , Abdullah, K., Lim. H. S., (2003). Malaysian Tiungsat-1 Imagery for Water Quality Mapping. http://www.gisdevelopment.net/application/nrm/water/quality/watq0005.htm

Nasrabadi, N.M. and Choo, C.Y., (1992). Hopfield network for stereo vision correspondence. *IEEE transactions on neural networks*. 3,1:5-13, 1992.

Robinson,I.S., (1994). Satellite Oceanography"An Introduction for Oceanographers and Remote Sensing Scientists". Second Edition, J*ohn Wiley & Sons, New York.*

Wang,L., Zhang, Y. and Zhang, Y. (1993). On absolute stability for a class of nonlinear control systems with delay, *Chin. Sci. Bull.* **38** (16), pp. 1445–1448.

Zhang, Y., Heng., P.A. and Fu, A.W.C. (1999). Estimate of exponential convergence rate and exponential stability for neural networks, *IEEE Trans. Neural Networks* **10** (6), pp. 1487–1493.

Zhao, H., (2004). Global asymptotic stability of Hopfield neural network involving distributed delays, *Neural Networks* **17** , pp. 47–53.