RETRIEVING OF SEA SURFACE CURRENT VARIATIONS FROM SENTINEL-1A SATELLITE DATA

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ABSTRACT: This is first work is done on application of Sentinel-1A satellite data to Malaysian coastal waters. This aims at utilizing an optimization of Hopfield neural network to retrieve variation of sea surface current along Malaysian coastal waters. In doing so, multi-objective evolutionary algorithm based on Pareto front is used to minimize the error has produced due to non-linearity between Sentinel-1A satellite data and sea surface movements. The study confirms that the multi-objective evolutionary algorithm can produce seasonal variation of sea surface current with precise value of ±0.08 m/s. In conclusions, Sentinel-1A satellite data can be used as an excellent sensors for retrieving coastal current movements based on optimization of Hopfield neural network.

1. INTRODUCTION

Yet, there is no study has implemented Sentinel-1 A data satellite data in oceanography applications along the Malaysian coastal waters. Sentinel-1 A is newly lunched on April 03, 2014. The data have been delivered hold a great promises for wide Earth observation because its high spatial and temporal resolution. It is be interesting when this study to be the first work in utilization of Sentinel-1 A satellite archived data along Malaysian coastal waters. One of interesting topic is current flow which is required short revisit satellite cycle and high resolution. These can provide precisely information about current dynamic flow. In fact, ocean current is important for ship navigation, fishing, pollutant substances transport and sediment transport. Both optical and microwave sensors have been implemented to study ocean current flows. The measurements of ocean from space is based on the electromagnetic signal. Indeed, an electromagnetic signal of optical and microwave reflects from the sea carrying information about one of the primary observable quantities which are the color, the radiant temperature, the roughness, and the height of the sea (Marghany 2015a).

Synthetic aperture radar (SAR) is recognized as the potential tool for dynamic oceanography studies. Indeed, the sea surface dynamic features of sea surface current is key parameters for atmospheric-sea surface interactions. In this regard, the climate change, marine pollution and coastal hazardous are predominantly ruled by ocean current speed and direction (Inglada and Garello 2002). The principal concept to retrieve the sea surface current from SAR data is function of the Doppler frequency shift theory (Marghany 2009a). Incidentally, the orbital mobility of the ocean wave and surface current dynamic interactions can cause shifting of the radar signal in the azimuth direction i.e. the flight direction which is known as the Doppler frequency shift (Cao and Wang 2003). In truth, the surface current dynamic is virtual to the orbital movement and antenna rotation of the Synthetic aperture radar. Therefore, the Doppler frequency shift, count on the SAR antenna view angle which is virtual to the orbital trajectory rotation (Marghany 2009 b and Marghany 2011). Consequently, the relationship between the sea surface dynamic orbital movement and the SAR satellite orbital rotation would be nonlinear because of the Doppler effect (Inglada and Garello 2002). In literature, there are several mathematical algorithms which are based on physical models to retrieve sea surface current from SAR data. On other words, these algorithms are implemented to map the Doppler frequency spectra into the real ocean sea surface current speed. However, these techniques are restricted because of the nonlinear complexity of sea surface dynamic behaviors and radar signal. In this regard, the Doppler velocity has coarser resolution than radar cross section along the azimuth direction (Inglada and Garello 2002; Marghany 2009b and Marghany 2011).

In this paper, we address the question of retrieving sea surface current pattern from Sentinel-1 A satellite data. This is demonstrated using neural network technique. Hypotheses examined are: (i) Hopfield neural network based multi-objective optimization via Pareto dominance algorithm can be implemented to single data without needing to include sequential SAR data; (ii) multi-objective optimization via Pareto dominance can be used as procedures for eliminating inherent speckle from Sentinel-1 A data; and (iii); the nonlinearity of the Doppler frequency shift can be reduced multi-objective optimization via Pareto dominance.

2. DATA ACQUISITION

The data used within Hopfield algorithm consisted of (i) SAR data which is Sentinel-1 A; and (ii) and the real in-situ measurement during Sentinel-1 A overpassed.

2.1 Sentinel-1 Data

In this study, Sentinel-1 A data with single polarization VV have been used. Sentinel-1 is the European Radar Observatory, representing the first new space component of the GMES (Global Monitoring for Environment and Security) satellite family, designed and developed by ESA and funded by the EC (European Commission). Sentinel-1 is composed of a constellation of two satellites, Sentinel-1A (Figure 1) and Sentinel-1B, sharing the same orbital plane with a 180° orbital phasing difference.

Except for the ocean wave and current studies, which is a single polarization mode (HH or VV) with C-band, the SAR instrument has to support operations in dual polarization (HH-HV, VV-VH), requiring the implementation of one transmit chain (switchable to H or V) and two parallel receive chains for H and V polarization. The specific needs of the four different measurement modes with respect to antenna agility require the implementation of an active phased array antenna. For each swath the antenna has to be configured to generate a beam with fixed azimuth and elevation pointing. Appropriate elevation beamforming has to be applied for range ambiguity suppression. In addition, the incident angle is ranged between 20º-46º.

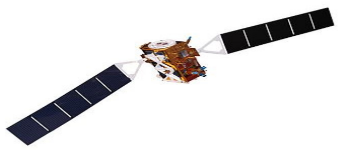

Figure 1. Sentinel-1 A satellite.

2.2 Real Sea Surface Current

The in situ sea surface current quantities i.e. speed and direction, are obtained using Acoustic Wave and Current (AWAC) (Figure 2) from the east coast of Kuala Terengganu, Malaysia on March 8th till 12th March 2015, at 5°28'02'' N and 103°07'48''E (Figure 3). AWAC recorded the water column current speed and directions.

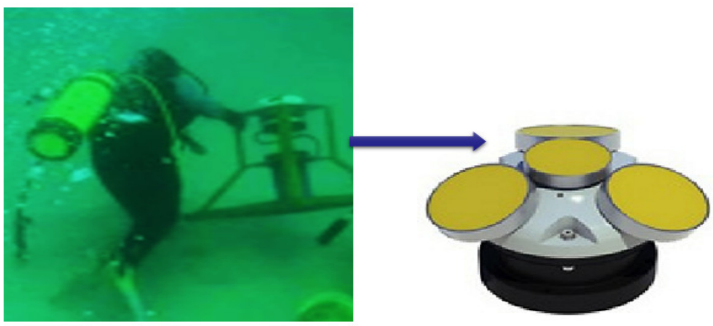

Figure 2. In-situ current measurement by AWAC

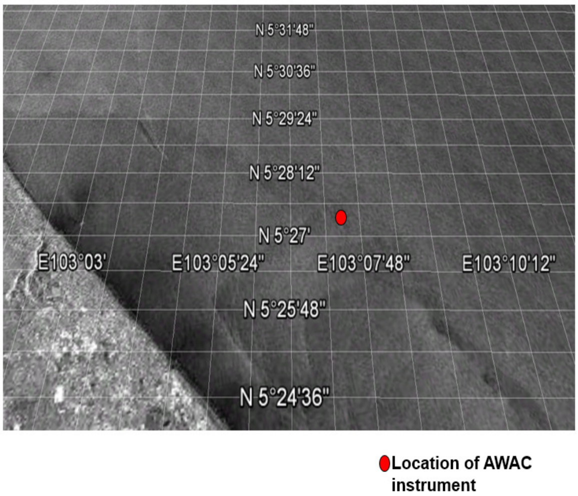

Figure 3. Geographical location of AWAC instrument.

According to Marghany (2009), data required from AWAC i.e. the sea current speed and direction, are collected as ASCII data which are used with to reduce the nonlinearity effects which caused by the Doppler shift spectra. These data are used to solve the nonlinearity of real ocean surface current and the Doppler frequency shift. Moreover, in situ data collection i.e. sea surface speed and direction, are also implemented to verify accuracy of proposed algorithm for sea surface current retrieving from Sentinel-1 A data.

2.3 Hopfield Algorithm

Marghany (2015b) have implemented Hopfield neural networks for RADARSAT-2 SAR data to retrieve sea surface current. This section has been retrieved from Marghany (2015b) work. Therefore, Hopfield neural networks is used with new satellite SAR sensor of Sentinel-1 A data. Consistent with 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 sea surface features, nonlinearity and the Doppler frequency shift (Marghany 2009a) 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*.

Following Marghany (2009b), Hopfield net is involved that $w_{ij} = w_{ji}$ and $w_{ii} = 0$. Succeeding, Cao and Wang, (2003), 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; and (iii) iterate until convergence and continue features tracking (Cote and Tatnall, 1997). First step of assign weight w_{ij} to synaptic connection can be achieved as understands:

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

Hopfield neural network could be identified current pattern features by mathematical comparing to each other in order to build an energy function (Liang and Wang, 2000 and Arik 2002). According to Côté and Tatnall (1997) the difference function to determine the discriminations between different features f_i, f_j by a given formula:

$$diff(f_i, f_j) = G.\max\left|\max(\frac{l_i}{l_j}, \frac{l_j}{l_i}) - L'', 0\right| + H.\max[\min|\theta_i - \theta_j|, 2\pi - |\theta_i - \theta_j| - \theta'', 0]$$
$$+ J.\max|dis_{ij} - dist'', \theta]| \quad (3)$$

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 θ is an angle of orientation of local curve element. In addition, $dist''$ and θ'' are the minimum acceptable distance and the maximum acceptable rotation angle, respectively before energy function.

2.3.1 Multi-objective Optimization

Following Atashkari et al., (2004), the Multi-objective optimization (MOB) which is also termed the multi-criteria optimization or vector optimization. In this regard, it has been defined as finding a vector of decision variables satisfying constraints to give acceptable values to all objective functions. Generally, it can be mathematically defined as: find the vector $S^* = \left[S_1^*, S_2^*, ..., S_n^*\right]^T$ to optimize

$$F(S) = \left[f_1(S), f_2(S), ..., f_k(S)\right]^T, \quad (4)$$

subject to *m* inequality constraints

$$g_i(S) \le 0 \quad , \quad \mathrm{i = 1 \ to \ m} \quad , \quad (5)$$

and *p* equality constraints

$$h_j(S) = 0 \quad , \quad \mathrm{j = 1 \ to \ p}, \quad (6)$$

where $S^* \in \Re^n$ is the vector of decision or design variables, and $F(S) \in \Re^k$ is the vector of objective functions which each of them be either minimized or maximized. However, without loss of generality, it is assumed that all objective functions are to be minimized.

A point $S^* \in \Omega$ (Ω is a feasible region in $\Re^n$ satisfying equations (4) and (6) is said to be Pareto optimal (minimal) with respect to the all $S \in \Omega$ if and only if $F(S^*) < F(S)$. Alternatively, it can be readily restated as $\forall i \in \{1,2,...,k\}, \forall S \in \Omega - \{S^*\} \ f_i(S^*) \le f_i(S) \wedge \exists j \in \{1,2,...,k\} : f_j(S^*) < f_j(S)$. In other words, the solution S^* is said to be Pareto optimal (minimal) of ocean current pattern if no other solution can be found to dominate S^* using the definition of Pareto dominance. For a given MOP, the Pareto front $\mathcal{PF}^*$ is a set of vector of objective functions which are obtained using the vectors of decision variables in the Pareto set $\mathcal{P}^*$, that is $\mathcal{PF}^*$ $= \{F(S) = (f_1(S), f_2(S), ..., f_k(S)) : S \in \mathcal{P}^*\}$. In other words, the Pareto front $\mathcal{PF}^*$ is a set of the vectors of objective functions mapped from $\mathcal{P}^*$ (Atashkari et al., 2004).

3. RESULTS AND DISUSSION

The Sentinel-1 A data with C_{VV}-band has used in this study. Figure 4 indicates the results which have been retrieved from Hopfield algorithm and Pareto algorithm. It is interesting to find that Pareto algorithm has find the best solution for sea surface current pattern as compared to Hopfield neural network (Figure 4b).The morphology of sea surface current structures are well identified using Pareto algorithm. Indeed, random generation of 1000 iterations within 3 min are required to achieve the performance of Pareto algorithm.

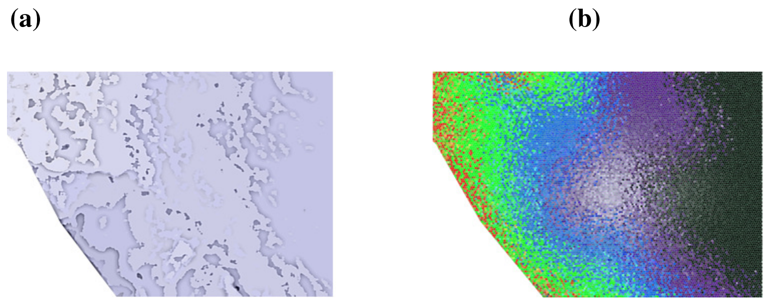

Figure 4. Ocean current pattern simulated from (a) Hopfield neural network result (b) Pareto optimal solution.

The current pattern is retrieved by Pareto optimal solution of Hopfield algorithm which demonstrates north-east flow i.e. 35°-45° with maximum velocity of 0.76 m/s. The current flows indicates a strong turbulent flow along the coastal water of Malaysia. This aggress with the studies of Mohd and Marghany (1996); Marghany (2000); Zelina et al., (2002); Marghany (2003); Marghany (2004); Marghany (2011a;2011b); Marghany (2012); Marghany (2013). In fact, the northeast current flow is a dominated feature along the coastal water of Kuala Terengganu, Malaysia during the northeast monsoon period (November to March).

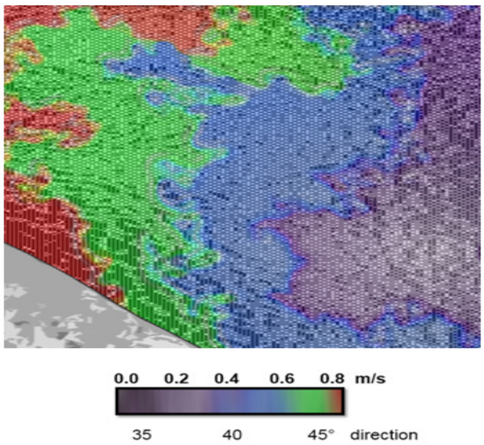

Figure 5. Sea surface current velocity based Pareto optimal solution.

The accuracy of this work is shown in Table 1. It is interesting to find that the Pareto optimal solution performances excellent that using Hopfield algorithm. This is clear with lower P value of 0.00005 and RMSE of ±0.08 and highest r^2 of 0.82. According to Marghany (2015b), the Hopfield neural network is contemplated as optimization tool to diminish the influence of the Doppler nonlinearity in the SAR images. Multi-objective optimization, consequently is considered as attaining a vector of decision variables sustaining constraints to provide precise consequences to all objective functions.

Table 1. Statistical regression of AWAC sea surface current and retrieved one by Hopfield neural network based Pareto optimal solution.

Methods	R^2	RMSE (m/s)	*P*
Hopfield neural network- AWAC	0.76	±0.2	0.0003
Pareto optimal solution-AWAC	0.82	±0.08	0.00005

Additionally, the multi-objective optimization via Pareto dominance obtains a precise curve that diminishes the inconsistency between the predictable sea surface current from Sentinel-1 A data and ground measurements. With this regard, the new approach based on Sentinel-1 A data and the multi-objective optimization via Pareto Dominance, can minimalize the quantity of the residual faults for retrieving sea surface current from Sentinel-1 A data and delivers precise sea surface current pattern variations. This work endorses the work done by Atashkari et al., (2014) and Marghany (2015b).

4. CONCLUSIONS

This work aimed at retrieving sea surface current from Sentinel-1 A data along the coastal water of Malaysia. Two approaches have been implemented Hopfield neural network algorithm and Pareto optimal solution. The study shows that the Pareto optimal solution has highest performance than Hopfield neural network algorithm with lowest RMSE of ±0.08. Further, Pareto optimal solution can determine the sea surface current pattern variation along coastal water from Sentinel-1 A data. In conclusion, Sentinel-1 A data shows an excellent promises for retrieving sea surface current with C_{vv}-band.

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