3-D visualizations of coastal bathymetry by utilization of airborne TOPSAR polarized data

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Multi-frequency C and L bands in the TOPSAR data have been utilized to reconstruct three-dimensional (3-D) bathymetry pattern. The main objective of this study is to utilize fuzzy arithmetic to reduce the errors arising from speckle in synthetic aperture radar (SAR) data when constructing ocean bathymetry from polarized SAR data. In doing so, two 3-D surface models, the Volterra algorithm and a fuzzy B-spline (FBS) algorithm, which construct a global topological structure between the data points, were used to support an approximation to the real surface. Volterra algorithm was used to express the non-linearity of TOPSAR data intensity gradient based on the action balance equation (ABC). In this context, a first-order kernel of Volterra algorithm was used to express ABC equation. The inverse of Volterra algorithm then performed to simulate 2-D current velocities from CVV and L HH band. Furthermore, the 2-D continuity equation then used to estimate the water depth. In order to reconstruct 3-D bathymetry pattern, the FBS has been performed to water depth information which was estimated from 2-D continuity equation. The best reconstruction of coastal bathymetry of the test site in Kuala Terengganu, Malaysia, was obtained with polarized L and C bands SAR acquired with HH and VV polarizations, respectively. With 10 m spatial resolution of TOPSAR data, bias of —0.004 m, the standard error mean of 0.023 m, $r^2$ value of 0.95, and 90% confidence intervals in depth determination was obtained with L HH band.

**Keywords:** TOPSAR polarized data; Volterra algorithm; fuzzy B-spline algorithm; bathymetry

1. Introduction

Coastal bathymetry is considered to provide key parameters for coastal engineering and coastal navigation. The bathymetry information is valuable for economic activities, security, and marine environmental protection. Single or multi-beam shipborne echo sounders are the classical systems used to map the sea bottom topography (Vogelzang et al. 1992, 1997, Hesselmans et al. 2000). Although these conventional techniques provide high precision results, they are very costly and time consuming, especially when large areas are being surveyed. Remote sensing methods in real time could be a major tool for bathymetry mapping which could produce synoptic data over large areas at comparatively low cost. However, the high speckle noise in synthetic aperture radar (SAR) images has posed great difficulties in

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inverting SAR images for determining coastal bathymetry. Speckle is a result of coherent interference effects among scatterers which are randomly distributed within each resolution cell. The speckle size is a function of the spatial resolution which induces errors in bathymetry signature detections. In order to reduce these speckle effects, appropriate filters, i.e. Lee, Gaussian, etc. (Lee et al. 2002), could be used in the pre-processing stage. The effectiveness of these speckle-reducing filters is, however, much influenced by local factors and application. In fact, all speckles in SAR images are related to local changes in the surface roughness. This can be due to direct reduction of the wave height (due to slicks), and roughness changes induced by winds (atmospheric effects) or wave-current interactions (fronts and bathymetry). By contrast, Yu and Scott (2002) stated several limitations of the speckle filtering approach. They reported that the size and shape of the filter window can affect the accuracy level of despeckle filters. For instance, a large window size would form a blurred output image, whereas a small window will decrease the smoothing capability of the filter and will leave speckle. They also found that window shape can induce changes in the physical characteristics of features in a SAR image. For instance, a square window (as is typically applied) will lead to corner rounding of rectangular features. In spite of despeckle filters performing edge enhancement, speckle in the neighborhood of an edge (or in the neighborhood of a point feature with high contrast) will remain after filtering. Furthermore, the thresholds used in the enhanced filters, although motivated by statistical arguments, are ad hoc improvements that only demonstrate the insufficiency of the window-based approaches. The hard thresholds that enact neighborhood averaging and identity filtering in the extreme cases lead to blotching artifacts from averaging filtering and noisy boundaries from leaving the sharp features unfiltered (Yu and Scott 2002).

SAR bathymetric mapping requires a standard filter processing to identify bathymetry features in SAR data. For instance, using the Lee filter could produce imperfect bathymetry signature detection. In fact, SAR data have discontinuities and lower gray-level gradients. In particular, Inglada and Garello (1999) stated that the anisotropic diffusion filter is more appropriate for speckle reduction in a SAR image. They concluded that the anisotropic diffusion filter produced the highest smoothed image as the anisotropic diffusion filter preserves the mean gray-level and maintains the bathymetry signature compared to the Lee filter. Nevertheless, Inglada and Garello (1999, 2002) were not able to state the accuracy rate of utilizing the Volterra model and anisotropic diffusion filter for SAR bathymetry reconstruction.

Several theories concerning the radar imaging mechanism of underwater bathymetry have been established, such as by Alpers and Hennings (1984), Shuchman et al. (1985), and Vogelzang (1997). The physical theories describing the radar imaging mechanisms for ocean bathymetry are well-understood as three stages: (1) the modulation of the current by the underwater features; (2) the modulation of the sea surface waves by the variable surface current; and (3) the interaction of the microwaves with the surface waves (Alpers and Hennings 1984). The imaging mechanism which reflects sea bottom topography in a given SAR image consists of three models. These models are a flow model, a wave model and the SAR backscatter model. These theories are the basis of commercial services which generate bathymetric charts by inverting SAR images at a significantly lower cost than conventional survey techniques (Wensink and Campbell 1997). In this context, Hesselmans et al. (2000) developed the Bathymetry Assessment System, a computer
program which can be used to calculate the depth from any SAR image and a limited number of sounding data points. They found that the imaging model was suitable for simulating a SAR image from the depth map. It showed good agreement between the backscatter in both the simulated and airborne-acquired images, when compared with accuracy (root mean square – rms) error of ±0.23 m within a coastal bathymetry range of 25–30 m. Recently, Li et al. (2009) utilized RADARSAT-1 and ENVISAT SAR images for mapping sand ridges with 30 m water depth. In doing so, they used modeled tidal current as input to an advanced radar-imaging model to simulate the SAR image at a given satellite look angle and for various types of bathymetry. In this context, they have acquired shallow-water current bathymetry in a two-dimensional (2-D) space. Finally, they reported that the sand ridge can only be imaged when strong ocean currents exist. On the contrary, Lyzenga et al. (2006) used a simple method of estimating water depths from multi-spectral imagery, based on an approximate shallow-water reflectance model. They found that a single set of coefficients derived from a set of IKONOS images produces good performance with an aggregate rms error of 2.3 m over all of the data sets. Coastal bathymetry mapping by using optical remote sensing data, however, can only be fully utilized in the clearest water, and considerably less in turbid water (Vogelzang et al. 1992). In fact, as the different wavelengths pass through the water column they become attenuated by the interaction with suspended particles in water (Mills 2006).

Recently, Splinter and Holman (2009) developed an algorithm to map nearshore bathymetry using a single aerial snapshot taken from a plane, unmanned aerial vehicle, or satellite. This algorithm is based on the changing direction of refracting waves which are used to determine underlying bathymetry gradients function of the irrotationality of wavenumber condition. In this context, Splinter and Holman (2009) claimed that depth dependences are explicitly introduced through the linear dispersion relationship. Furthermore, they used spatial gradients of wave phase and integrated times methods between sample locations (a tomographic approach) to extract wave number and angle from images. They found that synthetic bathymetries of increasing complexity showed a mean bathymetry bias of 0.01 m and mean rms of 0.17 m. Nevertheless, refraction-based algorithm has limitations in which it can be applied within 500 m away from the shoreline. In this circumstance, bathymetry of complex seas cannot be determined. This suggests that the refraction-based algorithm is best suited for shorter period swell conditions in intermediate water depths such as a semi-enclosed sea. Furthermore, the refraction-based algorithm cannot be implemented in SAR data. In fact, the shortest wavelength less than 50 m cannot be estimated in SAR data due to the limitation of using 2-D Fourier transform (Romeiser and Alpers 1997).

In this paper, we address the question of reducing the effect of speckle on the accuracy of depth determination in coastal waters using SAR data without needing to include any sounding data values. This is demonstrated with airborne SAR data (namely the TOPSAR) using integration of the Volterra kernel (Inglada and Garello 1999) and fuzzy B-spline (FBS) algorithm (Maged 2005, Maged et al. 2007). However, the studies of Maged and Hashim (2006) and Maged et al. (2007) have failed to acquire accurate bathymetry depth with single C_vv band, whereas the rms error is ±9 m. Four hypotheses are examined: (1) the Volterra model can be used to detect ocean surface current from TOPSAR polarized data; (2) there are significant differences between the different bands in detecting ocean currents; (3) the continuity
equation can be used to obtain the water depth; and (4) FBSs can be used to invert the water depth values obtained by the continuity equation into three-dimensional (3-D) bathymetry.

2. Methodology

2.1 Data set

SAR data acquired in this study were derived from the Jet Propulsion Laboratory (JPL) airborne Topographic SAR (TOPSAR) data. TOPSAR is a NASA/JPL multi-frequency radar imaging system aboard a DC-8 aircraft and operated by NASA's Ames Research Center at Moffett Field, USA. TOPSAR data are fully polarimetric SAR data acquired with HH, VV, HV, and VH-polarized signals from 5 m x 5 m pixels, recorded for three wavelengths: C band (5 cm), L band (24 cm), and P band (68 cm). The full set of C and L band have linear polarizations (HH, VV, HV), phase differences (HHVV), and circular polarizations (RR, RL). In addition, the TOPSAR sensor uses two antennas to receive the radar backscatter from the surface. The difference in arrival times of the return signals at the two antenna was converted into a modulo $-2\pi$ phase difference. Furthermore, TOPSAR data with C band provide digital elevation model with rms error in elevation ranging from about 1 m in the near range to greater than 3 m in the far range. A further explanation of TOPSAR data acquisition is given by Melba et al. (1999). This study utilizes both Cvv and LHH bands for 3-D bathymetry reconstruction because of the widely known facts of the good interaction between VV and HH polarization to oceanographic physical elements such as ocean wave, surface current features, etc. Elaboration of such further explanation can be found in Alpers and Hennings (1984) and Inglada and Garello (2002).

2.2 3-D coastal water bathymetry model

Two algorithms are involved for bathymetric simulation: the Volterra algorithm and the FBS algorithm. The Volterra algorithm is used to simulate the current velocity from TOPSAR data. The simulated current velocity is used with the continuity equation to derive the water depth variations under different current values. The FBS algorithm is used to reconstruct a 3-D chart from the 2-D water depth field (Figure 1).

2.3 Volterra algorithm

The Volterra algorithm can be used to express the SAR image intensity as a series of non-linear filters on the ocean surface current. This means that the Volterra algorithm can be used to study the image energy variation as a function of parameters such as the current direction, or the current magnitude. A generalized, non-parametric framework to describe the input–output $x$ and $y$ signals relation of a time-invariant non-linear system is provided by Inglada and Garello (1999). Furthermore, the input $x$ corresponds to the different TOPSAR band intensities, i.e. C and L bands, whereas $y$ corresponds to Volterra series of the different bands. In discrete form, the Volterra series for input, TOPSAR data intensities $X(n)$, and output of TOPSAR signals in the form of Volterra series, $Y(n)$ as given by Inglada

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and Garello (2002) can be expressed as:

\[
Y(n) = h_0 + \sum_{i_1}^{\infty} h_1(i_1)X(n - i_1) + \sum_{i_1}^{\infty} \sum_{i_2}^{\infty} h_2(i_1, i_2)X(n - i_1)X(n - i_2) \\
+ \sum_{i_1}^{\infty} \sum_{i_2}^{\infty} \sum_{i_3}^{\infty} h_3(i_1, i_2, i_3)X(n - i_1)X(n - i_2)X(n - i_3) \\
+ \ldots + \sum_{i_1}^{\infty} \sum_{i_2}^{\infty} \ldots \sum_{i_k}^{\infty} h_k(i_1, i_2, \ldots, i_k)X(n - i_1)X(n - i_2) \ldots X(n - i_k),
\]

where \( n, i_1, i_2, \ldots, i_k \) are discrete time lags. The function \( h_k \) \((i_1, i_2, \ldots, i_k)\) is the \( k \)-th order Volterra kernel characterizing the system. The \( h_1 \) is the kernel of the first-order Volterra functional, which performs a linear operation on the input and \( h_2, h_3, \ldots, h_k \) capture the non-linear interactions between input and output TOPSAR signals. In this context, the non-linearity is expressed as the relationship between different TOPSAR band intensities and ocean surface roughness. Consequently, surface current gradients in shallow waters can be imaged by TOPSAR different bands.
through energy transfer toward the waves. In fact, the radar system is restricted to measure surface roughness. The order of the non-linearity is the highest effective order of the multiple summations in the functional series.

Following Maged and Hashim (2006), Fourier transform is used to acquire non-linearity function from Equation (1) as given by:

\[ Y(v) = FT[Y(n)] = \int Y(n)e^{-j2\pi vn}dn \]  

(2)

where \( v \) is frequency and \( j = \sqrt{-1} \) (Maged and Hashim 2006). Domain frequency of TOPSAR image \( I_{\text{TOPSAR}}(v, \phi) \) can be described by using Equation (2) with the following expression:

\[ I_{\text{TOPSAR}}(v, \Psi_0) = FT[I(r, a)e^{j(R/V)u, u}(r, a)] \]  

(3)

where \( I(r, a) \) is the intensity TOPSAR image pixel of azimuth \( (a) \) and range \( (r) \), respectively, \( \Psi_0 \) is the wave spectra energy, and \( R/V \) is the range to platform velocity ratio, in case of TOPSAR equals 32 second(s) and \( u_a(r, a) \) is the radial component of surface velocities (Inglada and Garello 2002). Nevertheless, Equation (3) does not satisfy the relationship between TOPSAR data and ocean surface roughness. More precisely, the action balance equation (ABC) describes the relationship between surface velocity \( \vec{U} \), and its gradient and the action spectral density \( \psi \) of the short surface wave, i.e. Bragg wave (Alpers and Hennings 1984). In reference to Inglada and Garello (1999), the expression of ABC into first-order Volterra kernel \( H_1(v_a, v_r) \) of frequency domain for the current flow in the range direction can be described as:

\[
H_1(v_a, v_r) = k_r \langle \vec{U} \rangle \vec{u} \left[ \hat{K}^{-1} \left( \frac{\partial \psi}{\partial k} + \frac{\partial c^*_g}{\partial x_a} \vec{u} + \frac{\partial \vec{u}}{\partial y_r} v_r + 0.5u_a \right) \right] \frac{[\partial \vec{u}]}{[\partial \omega]}
\]

(4)

where \( \langle \vec{U} \rangle \) is the mean current velocity, \( \vec{u} \) is the current flow along the range direction while \( \vec{u}_a \) is the current gradient along the azimuth direction. \( K_r \) is the wave number along the range direction, \( \hat{K} \) is the spectra wave vector, \( \omega_0 \) is the angular frequency, \( c^*_g \) is the group velocity, \( \psi \) is the wave spectra energy, \( v \) stands for the Volterra kernel frequency along the azimuth and range directions, and \( R/V \) is the range to platform velocity ratio, in the case of TOPSAR equals 32 s.

Then, the domain frequency of TOPSAR data \( I_{\text{TOPSAR}}(v, \phi) \) can be expressed by using Volterra model for ABE into Equation (3):

\[ I_{\text{TOPSAR}}(v, \Psi) = FFT \left[ \left( \Psi_0(a, r) + \int Y(n) \right) \sum_{N=0}^{+\infty} \frac{1}{n!} \left( j\frac{R}{V}u_a(a, r) \right)^N \right] \]  

(5)

where \( N = 1, 2, 3, \ldots k \) and \( I_{\text{TOPSAR}}(v, \phi) \) represents Volterra kernels for the TOPSAR image in frequency domain which can be used to estimate mean current flow \( \vec{U}_r(0, r) \) in the range direction \( (r) \) with the following expression (Inglada and Garello 2002):

\[ I_{\text{TOPSAR}} = \vec{U}_r(0, r) \cdot H_1(v_a, v_r). \]  

(6)
The mean current movement along the range direction can be calculated by using the formula proposed by Vogelzang et al. (1997):

\[
\hat{U}_r(v_a, v_r) = \frac{\text{FFT} \left[ \prod_{j=1}^{N} I_{\text{TOPSISARV}(t)} \right]}{H_{1r}(v_a, v_r)},
\]

where \(\text{FFT} \left[ \prod_{j=1}^{N} I_{\text{TOPSISARV}(t)} \right]\) is the linearity of the Fourier transform for the input TOPSAR image intensity \(I_{\text{TOPSISARV}(t)}\), i.e. \(t\) is time domain. The inverse filter \(P(v_a, v_r)\) is used since \(H_{1r}(v_a, v_r)\) has a zero for \(\hat{U}_r(v_a, v_r)\) which indicates that the mean current velocity should have a constant offset. The inverse filter \(P(v_a, v_r)\) can be given as:

\[
P(v_a, v_r) = \begin{cases} [H_{1r}(v_a, v_r)]^{-1} & \text{if } (v_a, v_r) \neq 0, \\ 0 & \text{Otherwise} \end{cases}
\]

Then, the continuity equation is used to estimate the water depth as given by Vogelzang et al. (1992):

\[
\frac{\partial \zeta}{\partial t} + \nabla \cdot ((d + \zeta)\hat{U}_r(0, v_r)) = 0
\]

where \(\zeta\) is the surface elevation above the mean sea level, which is obtained from the tidal table, \(t\) is the time, and \(d\) is the local water depth. The real current data were estimated from the Malaysian tidal table of 6 December 1996.

### 2.4 The fuzzy B-splines (FBS) method

The FBSs are introduced allowing fuzzy numbers instead of intervals in the definition of the B-splines. Typically, in computer graphics, two objective quality definitions for FBSs are used: triangle-based criteria and edge-based criteria. A fuzzy number is defined using interval analysis. There are two basic notions that we combine together: confidence interval and presumption level. A confidence interval is a real values interval which provides the sharpest enclosing range for current gradient values. An assumption level \(\mu\)-level is an estimated truth value in the \([0,1]\) interval on our knowledge level of the gradient current (Anile 1997). The 0 value corresponds to minimum knowledge of gradient current and 1 corresponds to the maximum gradient current. A fuzzy number is then prearranged in the confidence interval set, each one related to an assumption level \(\mu \in [0,1]\). Moreover, the following must hold for each pair of confidence intervals which define a number: \(\mu > \mu' \Rightarrow d > d'\). Let us consider a function \(f:d \rightarrow d'\), of \(N\) fuzzy variables \(d_1, d_2, \ldots, d_N\). Where \(d_0\) is the global minimum and maximum values of the water depth of the function on the current gradient along the space. Based on the spatial variation of the gradient current and water depth, the FBS algorithm is used to compute the function \(f\).

Let \(d(i,j)\) be the depth value at location \(i,j\) in the region \(D\), where \(i\) is the horizontal and \(j\) is the vertical coordinates of a grid of \(m\) times \(n\) rectangular cells. Let \(N\) be the set of eight neighboring cells. The input variables of the fuzzy are the amplitude differences of water depth \(d\) defined by Anile et al. (1997):

\[
\Delta d_N = d_i - d_0, \quad N = 1, \ldots, 8
\]
where the \( d_i \), \( N = 1 \ldots 8 \) values are the neighboring cells of the actually processed cell \( d_0 \) along the horizontal coordinate \( i \). To estimate the fuzzy number of water depth \( d_j \) which is located along the vertical coordinate \( j \), we estimated the membership function values \( \mu \) and \( \mu' \) of the fuzzy variables \( d_i \) and \( d_j \), respectively, by the following equations described by Rövid et al. (2004):

\[
\mu = \max \{ \min \{ m_{pl}(\Delta d_i); d_i \in N_i \}; N = 1 \ldots 9 \}\tag{11}
\]

\[
\mu' = \max \{ \min \{ m_{LN}(\Delta d_i); d_i \in N_i \}; N = 1 \ldots 9 \}\tag{12}
\]

where \( m_{pl} \) and \( m_{LN} \) correspond to the membership functions of fuzzy sets. From Equations (11) and (12), one can estimate the fuzzy number of water depth \( d_j \):

\[
d_j = d_i + (L - 1)\Delta \mu
\]

where \( \Delta \mu \) is \( \mu - \mu' \) and \( L = \{ d_1 \ldots d_N \} \). Equations (12) and (13) represent water depth in 2-D, in order to reconstruct fuzzy values of water depth in 3-D, then fuzzy number of water depth in \( z \) coordinate is estimated by the following equation proposed by Russo (1998):

\[
d_z = \Delta \mu \text{MAX}\{ m_{LA}[d_{i-1,j} - d_{ij}], m_{LA}[d_{ij-1} - d_{ij}] \}\tag{14}
\]

where \( d_z \) fuzzy water depth values in \( z \) coordinate which is a function of \( i \) and \( j \) coordinates i.e. \( d_z = F(d_i, d_j) \). Fuzzy number \( F_\Omega \) for water depth in \( i, j \) and \( z \) coordinates then can be given by:

\[
F_\Omega = \{ \min(d_{z_1}, \ldots, d_{z_m}), \max(d_{z_1}, \ldots, d_{z_m}) \ treatments, FBS is introduced. Besides having the control point as in the B-spline, FBS also provides a set of weight parameters \( w_{ij} \) that exert more local shape controllability to achieve projective invariance. Following Fuchs et al. (1977) and Russo (1998), FBS surface that is composed of \( (O \times M) \) i.e. \( O \) and \( M \) are the element vectors that belong to knot \( p \) and \( q \), respectively, patches is given by

\[
\beta_{i,p}(r) = \begin{cases} 1 & \text{if } r_i \leq r \leq r_{i+1}, \\ 0 & \text{otherwise} \end{cases}
\]

\[
\beta_{i,p}(r) = \frac{r - r_i}{r_{i+1} - r_i} \beta_{i,p-1}(r) + \frac{r_{i+p} - r}{r_{i+p} - r_{i+1}} \beta_{i+1,p-1}(r) \quad \text{for } P > 1
\]
\[
S(p, q) = \sum_{i=0}^{M} \sum_{j=0}^{O} F_{ij} C_{ij} \beta_{i4}(p) \beta_{j4}(q) w_{ij} = \sum_{i=0}^{M} \sum_{j=0}^{O} F_{ij} S_{ij}(p, q) \quad (18)
\]

\(\beta_{i4}(P)\) and \(\beta_{j4}(q)\) are two basis B-spline functions, \(\{C_{ij}\}\) is the bidirectional controls net and \(\{w_{ij}\}\) are the weights. The curve points \(S(p, q)\) are affected by \(\{w_{ij}\}\) in case of \(P \in [r_i, r_{i+1}]\) and \(q \in [r_j, r_{j+1}]\), where \(P\) and \(P'\) are the degree of the two B-spline basis functions constituting the B-spline surface. Two sets of knot vectors are \(\text{knot } p = [0,0,0,1,2,3,\ldots,M,M,M,M]\), and \(\text{knot } q = [0,0,0,1,2,3,\ldots,M,M,M,M]\). Fourth-order B-spline basis are used \(\beta_{i4}(\cdot)\) to ensure continuity of the tangents and curvatures on the whole surface topology including at the patches boundaries.

The construction begins with the same pre-processing aimed at the reduction of measured current values into a uniformly spaced grid of cells. As in the Volterra algorithm, data are derived from the TOPSAR polarized backscatter images by the application of a 2-D fast Fourier transform (2-DFFT). First, each estimated current data value in a fixed kernel window size of 512 x 512 pixels and lines is considered as a triangular fuzzy number defined by a minimum, maximum, and measured value. Among all the fuzzy numbers falling within a kernel window size, a fuzzy number is defined whose range is given by the minimum and maximum values of gradient current and water depth along each kernel window size. Furthermore, the identification of a fuzzy number is acquired to summarize the estimated water depth data in a cell and it is characterized by a suitable membership function. The choice of the most appropriate membership is based on triangular numbers which are identified by minimum, maximum, and mean values of water depth estimated by continuity equation. Furthermore, the membership support is the range of water depth data in the cell and whose vertex is the median value of water depth data (Anile et al. 1997).

2.5 Statistical accuracy estimation

In order to evaluate the simulation method quantitatively, the regression model and rms were computed for the simulated bathymetry from TOPSAR data and bathymetry points extracted from a bathymetric chart of 1998, sheet number 4365 of 1:25,000 scale (Maged 1994). The critical issue of the simulated bathymetry map from airborne TOPSAR polarized data is accuracy. Through recent study, the accuracy of the simulated TOPSAR bathymetry is acquired by the standard error of mean and bias. The exact protocol which is used to implement the equations of the standard error of estimate and bias is involved forming several pseudo replicates of the bathymetry samples at exactly the same locations for the ground truth data and simulated data. In this context, the standard errors (i.e. difference between simulated and reference bathymetry) and bias are computed for each grid point resolution of 200 m and then averaged over all grid points having the same range of distance to coast, within 500 m intervals. In fact, the pixel resolution of
the TOPSAR data is 10 m × 10 m. Following McBean and Rovers (1998), the standard error of the estimate ($\sigma_{\text{est}}$) is defined as follows:

$$\sigma_{\text{est}} = \sqrt{\frac{\sum (d_g - d_{\text{TOPSAR}})^2}{N}}$$  \hspace{1cm} (19)

where ($\sigma_{\text{est}}$) is the standard error of the estimate, $d_g$ is ground truth bathymetry data acquired from a Topography map, $d_{\text{TOPSAR}}$ is the simulated TOPSAR bathymetry from C and L bands polarized data, and $N$ of grid points which equals 1000 samples. Following Hesselmans et al. (2000), bias is estimated as the average difference between ground data and simulated bathymetry data. Therefore, in order to obtain the bias $\epsilon$ on the simulated TOPSAR bathymetry, the following equation is used

$$\epsilon = \frac{\sum_{i=1}^{N} (d_{\text{TOPSAR}} - d_g)}{N}$$  \hspace{1cm} (20)

where $d_{\text{TOPSAR}}$ is the retrieved bathymetry from TOPSAR C and L bands polarized data; $d_g$ is the reference ground data on the number of grid points 1 to $N$.

3. Results

The TOPSAR polarized data used to reconstruct 3-D bathymetry which was acquired near the east coast of Peninsular Malaysia on 6 December 1996 (Figure 2). The TOPSAR C_{VV} and L_{HH} data covered an area located inbetween 103° 5’ E to 103° 9’ E and 5° 20’ N to 5° 27’ N. Further, Figure 2 shows the regions of interest that were used to simulate the bathymetric information from C band with VV polarization and L band with HH polarization. The bathymetry signature information has been extracted from five sub-images, where each sub-image was 512 × 512 pixels. Figure 3 shows the

Figure 2. Selected window sizes of A–D with 512 × 512 pixels.
signature of the underwater topography. The signature of underwater topography is obvious as frontal lines parallel to the shoreline. The backscattered intensity is damped by $-2$ to $-10$ dB in L band with HH polarization and $-6$ to $-14$ dB in C band with VV polarization data (Figure 3).

Comparison between Figures 4 and 5 showed that the $L_{HH}$ band captured a stronger current flow than the $C_{VV}$ band. The maximum current velocity simulated from the $L_{HH}$ band is $1.6 \text{ m s}^{-1}$ while the one simulated from the $C_{VV}$ band is $1.4 \text{ m s}^{-1}$. The main current direction was toward the south and approximately moving parallel to the shoreline (Figures 4 and 5). In addition, it is obvious that both bands are imagined in the current flow along the range direction.

Figure 6 shows the comparison between the 3-D bathymetry reconstruction from the topographic map, the $L_{HH}$ band data, and the $C_{VV}$ band data. It is obvious that

Figure 3. Bathymetry signature with different bands.

Figure 4. Current vectors simulated from the $C_{VV}$ band.
the coastal water bathymetry along the Sultan Mahmud Airport has a gentle slope and the bathymetric contours are parallel to the shoreline. Close to the river mouth, the bathymetry at this location shows a sharp slope. The L_{HH} band captured a more real bathymetry pattern than the C_{VV} band. This result could be confirmed using a linear regression model. In this context, Figure 7(a) shows the regression relation between the observed bathymetry and the results obtained using the C_{VV} band TOPSAR data. Figure 7(b) shows a similar regression relationship for L_{HH} TOPSAR data. The scatter points in Figure 7b are more close to the regression line than those in Figure 7(a). The bathymetry simulation from the L_{HH} band with an $r^2$ value of 0.95 and accuracy (rms) of $\pm 0.023$ m is more accurate than that obtained by using the C_{VV} band with accuracy of (rms) $\pm 0.03$ m. Figure 8 illustrates descriptive error bars of median and confidence intervals, respectively. The descriptive error bars of median represents the box-and-Whisker plots (Figure 8a) to assess and compare the bathymetry sample distributions that are identified as A, B, C, D, and F (Figure 6). Figure 8a shows that the L_{HH} band has a similar median value of 1.95 m to real bathymetry data as compared to the C_{VV} band. In addition, the top of the box in Figure 8a confirms that 75% of the L_{HH} band and real bathymetry values are less or equal to 1.95 m. To further confirm that the L_{HH} band has a higher performance than the C_{VV} band, the error bars are presented in Figure 8b. It is interesting to find that L_{HH} has a 95% confidence interval which extends from 9.17 m to 12.72 m which is approximately similar to real bathymetry data as compared to the C_{VV} band data. In contrast, Figure 8b confirms the C_{VV} band differs from real bathymetry map. In fact, the C_{VV} band has 95% of its bathymetry data are unlike real bathymetry data.

Finally, a difference statistical comparison confirms the results of Figures 7 and 8. Table 1 shows the statistical comparison between the simulated bathymetry from the C and L bands with real water bathymetry. This table represents the bias (average value of difference between bathymetry values simulated by TOPSAR polarized band and real water bathymetry); mean standard error, 90 and 95% confidence intervals, respectively. It can be noticed that the L_{HH} band performance has bias of $-0.004$ m, lower than the C_{VV} band. Therefore, L_{HH} has a standard error of mean
Figure 6. Three-dimensional bathymetry reconstructions from (a) real topography map, (b) $L_{HH}$ band, and (c) $C_{VV}$ band.
of ±0.023 m, lower than the CVV band. Overall performance of the L HH band is better than that of the CVV band which is validated by a lower range of error (0.06–0.26 m) with 90% confidence intervals (Table 1).

4. Discussion

The results show the potential of TOPSAR data for ocean bathymetry reconstruction where TOPSAR L HH band backscatter across bathymetry signature pixels agrees satisfactorily with previous published results (Vogelzang et al. 1992, Inglada and Garello 1999, Maged et al. 2007). This is due to the fact that the ocean signature of the boundary is clear in the brightness of a radar return, since the backscatter tends to be proportional to wave height (Vogelzang et al. 1992). In the C band with VV polarization, this feature is clearly weaker than at the L band with HH polarization. In fact, the L HH band has a higher backscatter value of 2 dB than the CVV band. In this context, it is possible that the character of the current gradient is such that the L HH band surface Bragg waves are more strongly modulated than for the CVV band. This may provide an explanation for weaker bathymetric signatures at the CVV band. The finding is similar to that of Romeiser and Alpers (1997).

Both bands showed that the southerly current flow is along the range direction. This is because December represents the northeast monsoon period as the coastal
water currents in the South China Sea tend to move from the north toward the south (Maged 1994, 2005, Maged and Hashim 2006, Maged et al. 2007). The range traveling current is caused by the weak non-linearity due to the smaller value of \( R/V \) which is 32 s. The weak non-linearity was assisted by the contribution of the linear Volterra kernels of the range current. This means that the range current will be equal

Table 1. Statistical comparison between the C\(_{vv}\) and the L\(_{HH}\) bands for coastal bathymetry reconstruction.

<table>
<thead>
<tr>
<th>Statistical parameters</th>
<th>TOPSAR bands</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C(_{VV}) band (m)</td>
</tr>
<tr>
<td>---</td>
<td>Lower</td>
</tr>
<tr>
<td>Bias</td>
<td>3.0</td>
</tr>
<tr>
<td>Standard error of the mean</td>
<td>0.5</td>
</tr>
<tr>
<td>90% (90% confidence interval)</td>
<td>0.55</td>
</tr>
<tr>
<td>95% (95% confidence interval)</td>
<td>0.3</td>
</tr>
</tbody>
</table>
to zero when the Volterra kernels $H_1(x, v_x, v_y)$ of the frequency domain has a zero for $|v_x, v_y|$. However, the inversion of the linear kernel of the Volterra algorithm allowed us to map the current movements along the range direction. This result confirms the study of Inglada and Garello (1999). The results of the Volterra algorithm showed that there was an interaction between water flow from the mouth of the Kuala Terengganu River and the near South China Sea water flow which appeared to be close to the mouth of the Kuala Terengganu River (Maged 2005).

In addition, during the data acquisition time, the wind was blowing at about 8 m s$^{-1}$ from northeast and swell system was propagated from the northeast. In this context, the quality of bathymetry map simulated from C band degrades because the image modulation becomes weaker relative to the speckle noise, and they are smeared out over a larger area due to the effect of long waves, which also add noise. As L band data suffer less from these drawbacks, use of L band provides more accurate results. In fact L band has higher signal-to-noise ratio compared to C band. This confirms the study of Vogelzang (1997). Furthermore, the HH polarization has a larger tilt modulation compared to the VV polarization. Tilt modulation explains that the Bragg scattering is dependent on the local incident angle. The long wavelength of L band HH polarization modulate this angle, hence modifying the Bragg resonance wave length. It might be due to the fact that the first-order Bragg Scattering gives good results for long radar wavelengths (L band), but for shorter radar wavelength (C band) the effects of waves longer than the Bragg waves must be taken into account (Shuchman et al. 1985, Romeiser and Alpers 1997). This could be due to strong current flow from the mouth river of the Kuala Terengganu. This study confirms the studies of Maged (2005) and Li et al. (2009).

It is clear that involving FBS in 3-D bathymetric mapping has produced real bathymetry visualization. Therefore, the visualization of 3-D bathymetry is sharp with the different TOPSAR polarized bands and real data due to the fact that each operation on a fuzzy number becomes a sequence of corresponding operations on the respective $\mu$ levels, and the multiple occurrences of the same fuzzy parameters evaluated as a result of the function on fuzzy variables (Anile 1997, Anile et al. 1997). It is very easy to distinguish between smooth and jagged bathymetry. Typically, in computer graphics, two objective quality definitions for FBSs were used: triangle-based criteria and edge-based criteria. Triangle-based criteria follow the rule of maximization or minimization, respectively, of the angles of each triangle (Fuchs et al. 1977) which prefers short triangles with obtuse angles. This finding confirms the studies of Keppel (1975), Anile (1997), and Maged et al. (2009).

Further, Figure 6 shows a clear discrimination between smooth and rough bathymetry where the symmetric 3-D structure of the bathymetry of a segment of a connecting depth. This can be noticed in areas A, B, C, D, E in real and L$_{HH}$ band data compared to C$_{VV}$ band. Smooth sub-surfaces appear in Figure 6 where the near-shore bathymetric contour of 5 m (area E) water depth runs nearly parallel in 3-D space to the coastline which is clear in Figure 6. Further, statistical analysis using error bars (Figure 8) has confirmed that L$_{HH}$ band tends to get closer and closer to the true mean of real bathymetry map as compared to the C$_{VV}$ band data. A rough sub-surface structure appears in steep regions of 20 m water depth (areas of B, C, and D). This is due to the fact that the FBSs considered as deterministic algorithms which are described here optimize a triangulation only locally between two different points (Anile et al. 1995). This corresponds to the feature of deterministic strategies of finding only sub-optimal
solutions usually. The 3-D bathymetry construction is not similar to the study of Inglada and Garello (1999), such that in the latter the bathymetry was constructed in the shallow sand waves due to the limitation of the inversion of the linear kernel of the Volterra algorithm. The integration of the inversion of the Volterra algorithm with FBSs improved the 3-D bathymetry reconstruction pattern.

The result obtained in this study disagrees with the previous study by Inglada and Garello (1999, 2002) who implemented 2-D Volterra model to SAR data. 3-D object reconstruction is required to model variation of random points which are function of \( x, y, \) and \( z \) coordinates. It is incredible to reconstruct 3-D using two coordinates, i.e. \((x,y)\). In addition, finite element model is required to discretize 2-D Volterra and continuity models in the study of Inglada and Garello (1999, 2002) to acquire depth variation in SAR image without uncertainty. Previous studies done by Alpers and Hennings (1984), Shuchman et al. (1985), Romeiser and Alpers (1997), Vogelzang (1997), Hesselmans et al. (2000), and Li et al. (2009) were able to model spatial variation of sand waves. In this study, FBS algorithm produced 3-D bathymetry reconstruction without existence of shallow sand waves. In fact FBS algorithm is able to keep track of uncertainty and provide a tool for representing spatially clustered depth points. This advantage of FBS is not provided in Volterra algorithm and 1-D or 2-D continuity model.

The accuracy standards for hydrographical charting with acoustic or mechanical based sounding is defined as the total error of derived depths, should not exceed, with probability of 90%, \( \pm 0.3 \text{ m} \) for depths less than 30 m or 1% of the depths greater than 30 m (Mills 2006). This is in fact a very stringent requirement, and the derived bathymetric information from non-contact techniques including laser bathymetric sensors (Guenther et al. 2000) which at present are very much dependent on the clarity of water for achieving high accuracy as stipulated in International Hydraulic Organization (IHO). However, for a general survey to identify moving shoals within navigational channel or coasts, for large aerial reconnaissance, this technique demonstrates its potential at relatively low cost before detailed surveys can be carried out. In this context, the accuracy comparison between the recent results and IHO standards cannot be established due to the lack of sounding data in the study area. The accuracy of TOPSAR for 3-D bathymetry reconstruction can be improved by using more than one TOPSAR data during the data assimilation processing. In fact an increased number of TOPSAR data reduces the effect of speckle noise that TOPSAR data are acquired under different marine geophysical conditions such as tide and wave-current interactions which can provide other features of the bottom topography. Therefore, the combination of the different data within time variation could provide a more perfect bathymetry reconstruction. This agrees with studies by Forster (1985) and Hesselmans et al. (2000).

5. Conclusions

This work has demonstrated the 3-D bathymetry reconstruction from TOPSAR polarized data. The inversion of the Volterra algorithm was used to estimate the water current movements. Then, the continuity equation was used to estimate the water depth that was a function of mean water current velocity. Finally, the FBSs were used to reconstruct the bathymetry pattern. The study shows that the maximum current velocity simulated from the \( C_{VV} \) band was 1.4 m s\(^{-1}\) while the ones
simulated from the L_{HH} band was 1.6 m s^{-1}. This assisted the L_{HH} band to capture more accurately bathymetry features with \( r^2 \) value of 0.95, standard error mean of \( \pm 0.023 \) m. Further, L_{HH} has a similar pattern of real bathymetry which is indicated by a mean difference value of 0.004 m and the 95% confidence interval extends from 9.17 m to 12.72. It can be said that the L_{HH} band provides a better approximation to the real bathymetry than does the C_{VV} band. In conclusion, the integration between the Volterra algorithm and the FBSs could be an excellent tool for 3-D bathymetry determination from SAR data.

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