Article

BRIDGING GPS OUTAGES USING SPECTRAL FUSION AND NEURAL NETWORK MODELS IN SUPPORT OF MULTIBEAM HYDROGRAPHY.

By A. EL-ASSAL (Egypt), A. EL-RABBANY (Canada)
and S. M. ABDELRAHMAN (Egypt)
Arab Academy for Science and Technology and Maritime Transport, Egypt
Ryerson University, Toronto, Canada

Abstract

In classical hydrographic surveying, the use of GPS is limited to providing horizontal control for survey vessels. More recently, an alternative practice has evolved, which determines depth values relative to a geodetic datum and then relate them to tidal datums through a series of vertical datum transformations. Although it has a number of advantages over classical hydrographic surveying, this practice requires accurate 3D positioning information. Unfortunately, accurate 3D positioning solution may not always be available as a result of communication link problems, GPS outages, or unsuccessful fixing for the ambiguity parameters. This paper examines the use of wavelet analysis to spectrally combine the GPS/INS height data series and the heave signal to bridge the height data gaps. In addition, a neural network-based model is developed to precisely predict the horizontal component of the survey vessel.

Résumé

Dans les levés hydrographiques classiques, l'utilisation du GPS est limitée à la fourniture d'un contrôle horizontal pour les bâtiments hydrographiques. Plus récemment, une autre pratique est apparue et celle-ci détermine les valeurs de profondeur par rapport à un système géodésique puis les rapporte au niveau de référence des marées par le biais d'une série de transformations du système géodésique vertical. Bien que ceci offre un certain nombre d'avantages par rapport aux levés hydrographiques classiques, cette pratique nécessite des informations exactes sur la détermination de la position en 3D. Malheureusement, une solution exacte de détermination de la position en 3D n'est pas toujours disponible à cause de problèmes de liaison en matière de communications, de défaillances GPS, ou de réparation infructueuse des paramètres d'ambiguïté. Le présent article examine l'utilisation d'une analyse des ondelettes pour combiner de manière spectrale les séries de données de hauteur GPS/INS et le signal de pilonnement afin de combler les lacunes en données de hauteur. En outre, un modèle inspiré d'un réseau neuronal est en cours de développement en vue d'une prédiction précise de la composante horizontale du bâtiment hydrographique.

Resumen

En los levantamientos hidrográficos clásicos, el uso del GPS está limitado al suministro de control horizontal para los buques hidrográficos. Más recientemente, se ha desarrollado una práctica alternativa, que determina los valores de la profundidad relativos a un datum geodésico y los relaciona posteriormente con los datums de mareas a través de una serie de transformaciones del datum vertical. Aunque tiene una serie de ventajas con respecto a los levantamientos hidrográficos clásicos, esta práctica requiere una información precisa del posicionamiento en 3D. Desgraciadamente, puede que una solución de posicionamiento preciso en 3D no esté siempre disponible como resultado de los problemas de enlaces de datos, los cortes GPS, o un ajuste infructuoso de parámetros de ambigüedad. Este artículo examina el uso de un análisis de ondas pequeñas para combinar espectralmente la serie de datos de altura GPS/INS y la señal de oleaje para superar las deficiencias de datos de alturas. Además, se ha desarrollado un modelo basado en la red neural para predecir con precisión la componente horizontal del buque hidrográfico.

Introduction

The current state of technology in hydrographic surveying makes use of multibeam echo-sounding systems, which provide digital hydrographic data with near-full coverage of the seabed. Traditionally, in multibeam hydrography, the use of GPS has been limited to providing horizontal positioning of the survey vessel. Depth values relative to tidal datum were obtained using the bathymetric data corrected for a number of vertical translations including vessel's draft, squat, settlement, heave and tide. Unfortunately, however, not all vertical translations can be accurately measured or modelled, which affects the accuracy of the final hydrographic products. An alternative practice has recently evolved, which takes advantage of the improved 3D positioning, attitude and heave solutions through the use of RTK-based GPS/INS systems. With this practice, depth values are determined relative to a geodetic datum and then are related to tidal datums through a series of vertical datum transformations. Unlike classical hydrographic surveying, vertical translations such as vessel's draft, squat, settlement and heave are not required with this practice. Unfortunately, although has a number of advantages over classical hydrographic surveying, this practice requires accurate 3D positioning information, which may not always be available as a result of communication link problems, GPS outages, or unsuccessful fixing for the ambiguity parameters. This paper examines the use of wavelet analysis to spectrally combine the GPS/INS height and heave data to obtain continuous, precise high-rate height information. It is shown that the maximum error in the case of a 60-second data gap is 9 cm, which indicates that the height data can be recovered with high accuracy even when relatively long data gaps are encountered. To recover the horizontal positioning component, a neural network-based prediction method was developed. A three-layer feedforward neural network trained with the back-propagation algorithm was employed for this purpose. It is shown that, for an outage period of 60 seconds, the maximum absolute errors in the easting and northing components are in the order of 2.1 cm and 4.3 cm, respectively.

Vessel Positioning and Orientation

Traditionally, the vessel's heading (yaw) was measured by a mechanical gyrocompass (or a magnetic compass), while the roll, pitch and heave information were obtained from a motion sensor. Gyrocompasses provide heading measurements with an accuracy level of 0.75˚ or better. However, accuracy degradation can be expected under dynamic conditions or with the increase in the vessel's latitude. Magnetic compasses provide heading measurements at a relatively lower accuracy level (about 1-2 degrees or less). The first generation motion sensors employed a two-axis damped pendulum to obtain the pitch and roll information and a vertical accelerometer to obtain the heave information. That series of motion sensors was succeeded by another series, which used the measurements of a strapdown array of tri-axial linear accelerometers and three angular rate gyros to estimate the pitch, roll and heave. Unfortunately, both generations of motion sensors suffered from accuracy limitations. The most noticeable limitation is the incapability of those sensors to adequately measure the roll component in the presence of strong horizontal acceleration, as a result of, for example, sharp turns (Dinn and Loncarevic, 1994). Multi-antenna GPS systems were also developed in early 90s for the purpose of vessel attitude determination (Lachapelle et al., 1994). These systems have the advantage that they sense the attitude in a purely kinematical mode, which means that they are immune to external forces. This is particularly important when the survey vessel makes a sharp turn. They suffered, however, from some accuracy limitations; with the noise due to the short distances between the GPS antennas being the most challenging. According to Kleusberg (1995), the noise level increases by a factor of 10 if the distances between the antennas are reduced from 10 meters to one meter. Therefore, this method did not find wide acceptance within the hydrographic community.

More recently, a GPS-aided inertial navigation system was developed, which aimed at improving the positioning, attitude and heave solutions by taking advantage of the complementary nature of the GPS and the INS systems. This integration improved the accuracy and reliability of positioning, roll and pitch solutions significantly. However, the accuracy of the heading and heave solutions were relatively low. As shown by Skaloud (1995), the accuracy of the heading solution is limited by both the horizontal accelerometer biases and the gyro biases. To overcome this limitation, some manufacturers have recently developed integrated GPS/INS systems that utilize two GPS receivers and antennas, e.g., Applanix POS/MV systems and Seapath 200 RTK. The two GPS receivers are used to determine the initial GPS-based heading of the survey vessel, which is then blended with the inertial data to produce smoothed final heading information. Reported heading accuracy is in the order of 0.01° (1s) for a 4m antenna separation, which is about one order of magnitude better than that of the single GPS-aided INS system. A newer version of Applanix system, POS/MV Elite, was recently introduced, which does not require a second GPS receiver to obtain high-accuracy heading (Applanix, 2009). To achieve this, the POS/MV Elite system uses a higher grade inertial measurement unit (IMU) than predecessor.

Unfortunately, although state-of-the-art RTK-based GPS/INS systems meet the IHO specifications under normal operation conditions, they may not do so under GPS outages. For example, although the recently developed Applanix POS/MV Elite provides sub-decimeter-level accuracy under normal operation conditions, its accuracy is reported to deteriorate to 0.5m (1s) after a 60-second GPS outage (Applanix, 2009).

In fact, the accuracy deteriorates at a much higher rate with longer GPS outage as a result of the INS drift. Considering a 60-second GPS outage and given that the vertical positioning component is always worse than the horizontal component, the POS/MV Elite system may not meet the vertical uncertainty requirements of IHO Special Order. In addition, depending on the water depth and the accuracy of other vertical translations, the vertical uncertainty requirements of IHO Order 1 may not be met as well. Other systems on the market are expected to have a similar or a poorer performance.

Wavelet Analysis

A wavelet is a waveform of finite interval and zero mean (Mathworks, 2002). Wavelet analysis is a relatively new way of modeling and processing signals, which have traditionally been done by Fourier analysis. While Fourier analysis breaks up a signal into sine and cosine functions, wavelet analysis breaks up a signal into translated (i.e., shifted) and scaled versions of the original wavelet. Translating a wavelet means shifting it forward (or backward) in time. Scaling a wavelet, on the other hand, means stretching (or compressing) it to obtain low and high frequency wavelets. Smaller scale factors correspond to more compressed (or high frequency) wavelets and vice versa. There exist many wavelet families that can be used for various purposes, including Daubechies, Haar, Meyer, Morlet, and others. In this paper, we used the Daubechies (db) family of wavelets. There are some advantages of wavelet analysis over Fourier analysis, including the ability of the former to analyze non-stationary signals and signals with more localized features (Boggess and Narcowich, 2001; Mathworks, 2002).

A wavelet-based filtering is accomplished by first decomposing the signal to obtain the wavelet coefficients, both approximations and details. The approximations constitute the low-frequency constituents of the signal, while the details constitute the high-frequency constituents. It should be pointed out that a suitable decomposition level must be used, which would depend on the signal characteristics (Mathworks, 2002). Once the wavelet coefficients are obtained, the unwanted coefficients (i.e., details in the case of POS altitude and approximations in the case of heave) are removed or modified. The last step is to re-construct the signal using the approximation coefficients of the POS altitude data and the details coefficients of the heave signal.

Artificial Neural Network Model Development

Artificial Neural Networks (ANN), or simply neural networks, are computational models that imitate the human brain in performing a particular task (Haykin, 1999). They have the capability to solve complex problems through learning, or training, and then generalizing the network outputs for other inputs. A neural network consists of processing elements, or neurons, that are massively interconnected. Each of the connecting links is characterized by its own weight, or strength. Figure 1 represents a block diagram of a simple model of a neuron showing the weights of the various links. An activation function, such as a sigmoid function or a hyperbolic tangent function, is applied to limit the amplitude of the neuron. The sigmoid function is an s-shaped function, which is used widely in the construction of the neural networks (Haykin, 1999). The logistic function represents an example of the sigmoid function, which is defined as:

$$\varphi(v) = [1 + \exp(-av)]^{-1} \qquad (1)$$

where the parameter a represents the slope of the sigmoid function. Finally, an external bias, b_k, is applied to increase or lower the net input of the activation function. The neural network is trained to find the optimal values for the weights and the biases.

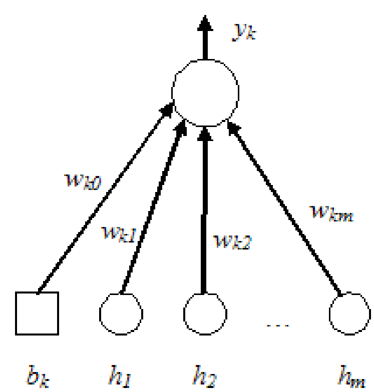

Figure 1. Simple neuron model

The above structure for a neuron k can be represented mathematically as:

$$v_k = \sum_{j=1}^{m} w_{kj}h_j + b_k = \sum_{j=0}^{m} w_{kj}h_j \qquad (2)$$

$$y_k = \varphi(v_k) \qquad (3)$$

where $h_0, h_1, h_2, \ldots, h_m$ are the input signals; v_k is the activation potential of neuron k; y_k is the output signal, and $w_{k0}, w_{k1}, w_{k2}, \ldots, w_{km}$ are the weights of neuron k. It should be noted in (2) that the values of $h_0 = +1$ and $w_{k0} = b_k$, respectively.

Neural networks can be designed in various ways, depending on how the neurons are structured and the learning algorithms, or rules, used. Network architectures may be classified as single-layer feedforward, multi-layer feedforward, and recurrent networks (Haykin, 1999).

Recurrent neural networks are similar to the feedforward networks, with the exception that the former have at least one feedback loop. According to Schuh et al. (2002), feedforward networks have better prediction capabilities than recurrent networks. In our prediction model, we used the feedforward neural networks. In this case, the output signal at a neuron j (either a hidden neuron or an output node) can be written as:

$$y_j(n) = \varphi(v_j(n)) \quad (4)$$

where $v_j(n)$ is the activation potential of neuron j, which is defined by:

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) y_i(n) \quad (5)$$

where m is the total number of inputs (without the bias) applied to neuron j; $w_{ji}(n)$ represents the weight connecting the output of neuron i to the input of neuron j at iteration n (n^{th} training example); and $y_i(n)$ is the output signal of neuron i (i.e., the input signal of neuron j). It should be clear that $y_i(n) = h_i(n)$, the i^{th} element in the input vector, if neuron j is in the first hidden layer.

Training a neural network is accomplished through iterative adjustments of the free parameters, i.e., the weights and bias, of the network till we obtain the optimal values. There exist various learning algorithms, which are fundamental to the design of neural networks. Of these, the back-propagation-learning algorithm is the most widely used for feedforward neural networks (Schuh et al., 2002), which is discussed here.

With the back-propagation-learning algorithm, the output signal of a neuron j, $y_j(n)$, is compared to a desired (target) output, $d_j(n)$. The error signal at the output of neuron j, $e_j(n)$, is defined as:

$$e_j(n) = d_j(n) - d_j(n) \quad (6)$$

where n represents the n^{th} training example (i.e., n^{th} pattern). The objective of the iterative adjustments is to make $y_j(n)$ as close as possible to $d_j(n)$, which can be achieved by minimizing a cost function (total instantaneous error energy over all neurons in the output layer) defined as:

$$\mathscr{E}(n) = \frac{1}{2} \sum_{j \in C} e_j^2(n) \quad (7)$$

where C represents all neurons in the output layer. The weight correction $\Delta w_{ji}(n)$ can now be defined according to the delta rule as (Haykin, 1999):

$$\Delta w_{ji}(n) = -\eta \frac{\partial \mathscr{E}(n)}{\partial w_{ji}(n)} = \eta \delta_j(n) y_i(n) \quad (8)$$

where η is the learning rate parameter; and $\delta_j(n)$ is the local gradient defined by:

$$\delta_j(n) = -\frac{\partial \mathscr{E}(n)}{\partial v_j(n)} = e_j(n) \varphi'_j(v_j(n)) \quad (9)$$

where $\varphi'_j(v_j(n))$ is the derivative of the associated activation function. This means that for $\delta_j(n)$ to exist, the activation function must be continuous, which is satisfied by both the sigmoid and hyperbolic tangent functions presented above.

The selection of the learning rate parameter η affects the rate of learning of the neural network. The smaller the value of η is, the smaller the changes in the weights and network rate of learning. Smaller η values result in smaller changes to the weights in the network, and consequently slower rate of learning. If, on the other hand, the η values are too large, the network may become unstable (i.e., oscillatory) and the algorithm diverges. To overcome this problem, the generalized delta rule is used, which introduces an additional term to (8) known as the momentum constant (see Haykin, 1999 for details).

The weights will be adjusted iteratively by presenting new epochs of training examples to the neural network. Unfortunately, there is no clear-cut criterion to decide when to stop the training, i.e., to consider that the back-propagation algorithm has converged (Haykin, 1999). If the training is not stopped at the right point, an over-fitting of the training data (i.e., model does not interpolate well between the points) might occur. One approach to address this problem is to create a test dataset, which tests the neural network for its generalization performance (NeuralWare, 2001).

Under certain circumstances, for example when encountering a prediction problem, it might be better to use the modular neural networks (NeuralWare, 2001). A modular neural network has the capability of dividing a problem into sub-problems and resolving each sub-problem rather well. It consists of a group of back-propagation networks, sometimes referred to as “local experts”, each has the same architecture. This group of networks compete to learn the various aspects of the problem, which is then controlled by a “gating network”. The number of local experts is determined by the number of output neurons of the gating network. In this work, a modular three-layer feedforward neural network trained using the back-propagation algorithm was selected to predict the horizontal position of the survey vessel during GPS outages.

Results and Discussion

To verify the proposed spectral fusion and neural network techniques, we used the 2005 Common Dataset, which was collected in Plymouth Sound, UK, in August 2004. POS/MV 320 RTK with a 4m antenna separation was used to provide reference positioning, attitude and heave data. A total of eight tracklines were used to verify the proposed technique. The results of one trackline are presented in this section as an example. Similar results were obtained for the other tracklines.

To ensure adequate results, preprocessing of the data was necessary. While the POS altitude data was sampled at approximately 0.1 sec, the heave data was sampled at approximately 0.02 sec (so were the roll and pitch). As such, we used the Matlab toolbox to interpolate the above data sets, along with the heading data, to bring them at exactly 0.02 sec sampling rate. It should be pointed out that the interpolated POS altitude data are only initial values for the high-rate altitude data. Obtaining precise high-rate altitude data, however, is dealt with at a later stage of processing as shown below. As well, gaps in the POS altitude data, which essentially result from the GPS outages, are left without interpolation. The second preprocessing step involved a time offset correction, which was detected between the POS altitude and heave data sets. To determine the time offset, we performed a cross-correlation analysis between the POS altitude and heave data sets. Figure 2 shows the correlation function for trackline 56. As can be seen in Figure 2, the peak of the cross-correlation function is shifted by 0.84 seconds, which indicates that there is a time shift between the two data sets. Table 1 shows the time shifts for all tracklines. Once determined, a time shift correction was applied to the POS altitude data. The final preprocessing step determined the altitude of the IMU reference point (RP) in the North-East-Down (NED) reference frame. This was achieved based on the WGS84 coordinates of the master shipboard GPS antenna, the sensor offsets (lever arm) and the vessel attitude parameters. This step enables the combination of the IMU RP altitude data and the heave signal.

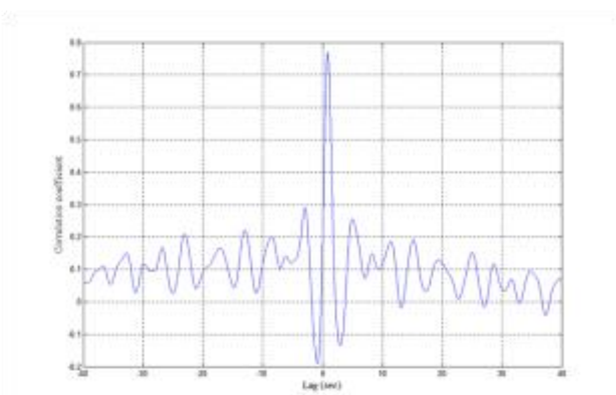

***Figure 2**. Cross-correlation function showing time shift*

Trackline	56	57	58	59	69	70	72	73
Time shift (sec)	0.84	0.00	0.22	0.46	0.24	0.92	0.20	0.06

***Table 1**. Time shift for all tracklines*

a. Height Recovery Results:

Artificial outages of 15, 30 and 60 seconds, respectively, were introduced to the continuous IMU RP altitude data series obtained above. As the heave signal represents the vertical translation relative to a local mean water level, we considered the line connecting the last point before an outage and the first point after the same outage as the heave datum. The recovered altitude value at any time during an outage is then obtained by adding the heave datum value, relative to WGS84, to the heave value at that time. Table 2 shows the minimum and maximum residual values (i.e. recovered minus reference) and the standard deviations for the various outages. As can be seen, the maximum residual values are less than 3cm and 9cm for outages of 30 and 60 seconds, respectively. This means that the altitude data can be recovered with high accuracy even for data gaps of up to 60 seconds.

Altitude data gap (seconds)	Residuals		Standard deviation (cm)
	Minimum value (cm)	Maximum value (cm)	
15	1.0	2.1	0.7
30	2.5	2.6	1.1
60	2.1	9.0	2.6

***Table 2**. Altitude residuals for various outage periods*

To obtain a precise high-rate altitude data we spectrally combined the heave data with the no-gap altitude data obtained above. In principle, this can be done by applying a high-pass filter to the heave data and a matching low-pass filter to the original (no-gap) altitude data. Adding the two filtered data sets produces the required high-rate altitude data. Traditionally, the Fourier transform is used for this purpose. However, since the heave signal is non-stationary, wavelet analysis might be a better choice. In this research we used the db1 wavelet family with a decomposition level of 3 for filtering both of the original altitude and heave data sets. The final high-rate, precise altitude data was then obtained through signal reconstruction using the approximations coefficients of the original altitude data and the details coefficients of the heave signal. Figures 3 and 4 show a comparison between the recovered high-rate altitude data obtained with the wavelet method and the correct (without the artificial gaps) altitude data. As can be seen in Figures 3 and 4, the two data sets match each other very closely, which proves that the wavelet method can effectively be used to recover the vessel altitude at a high rate.

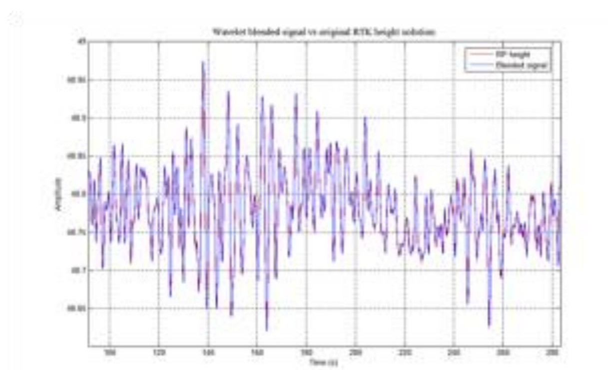

***Figure 3**. Recovered wavelet-based altitude*

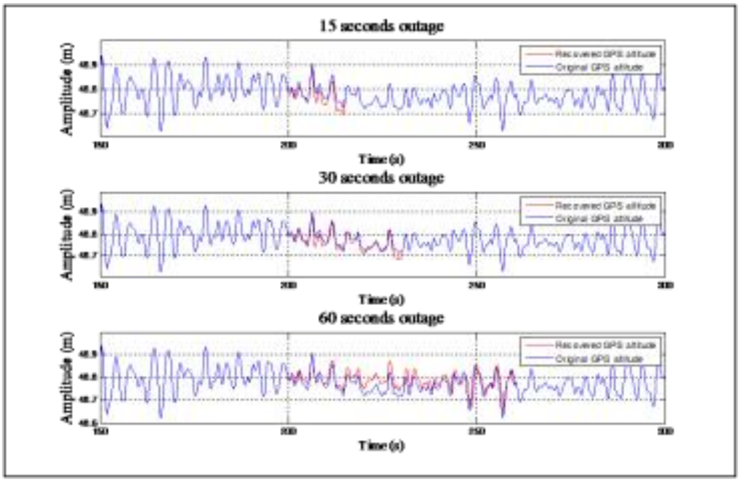

Figure 4. : *Recovered wavelet-based altitude for various outage periods.*

b. Horizontal Position Recovery Results:

In principle, predicting the horizontal position can be carried out using differential distance (i.e. distance travelled between two consecutive epochs) and heading data. However, examining the differential distance data series showed that it contains too many spikes, which result from missing values. This can confuse the neural network, which leads to incorrect results. To overcome this problem, we replaced the distance with the vessel speed, which is always uniform, and the time difference. The heading data were used as the third input to the neural network.

As indicated above, we used a modular three-layer feedforward neural network trained using the back-propagation algorithm to predict the horizontal position of the survey vessel during GPS outages. The structure of the neural network was built using the Matlab neural network toolbox.

Several tests were conducted to optimize the structure of the network.

It was concluded that the modular neural network with the structure 3-20-2] gives the best results, i.e., has the lowest root-mean-square (RMS) error. Similar to the height data, artificial outages of 15, 30 and 60 seconds, respectively, were introduced to the speed, differential time, and eading data sets. We used a 100-epoch segment of the speed, time difference, and heading data sets for training the neural network, while the network output was the easting and northing increments. Table 3 shows the ANN prediction results for the easting and northing components for the three artificial gaps. Figure 5 shows the northing and easting residuals for the various outages. As can be seen, the designed neural network was capable of predicting the northing and easting components at the centimeter level regardless of the outage duration.

Table 3. *Horizontal position residuals for various outage periods*

Horizontal Position data gap (seconds)	Easting Residuals		Northing Residuals	
	Mean value (cm)	Maximum value (cm)	Mean value (cm)	Maximum value (cm)
15	0.2	0.7	0.3	0.4
30	0.2	1.1	0.2	1.4
60	0.3	2.1	0.6	4.3

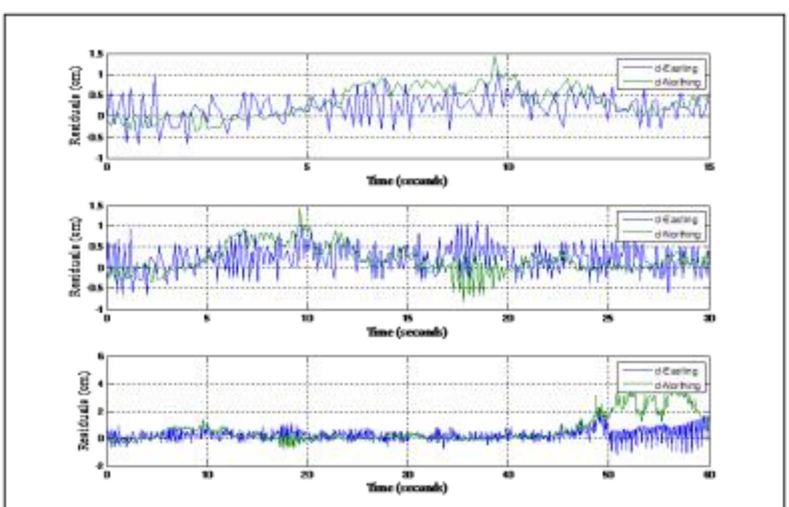

Figure 5. *Easting and northing residuals for various outage periods*

Conclusions

This paper examined the potential use of wavelet analysis and artificial neural networks to recover the vessel's 3D position. It has been shown that the 3D position can be recovered with high accuracy even for data gaps of up to 60 seconds. This allows for a number of applications to be developed, including the development of a seamless vertical reference system and coastal zone management.

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Biographies

Ashraf El-Assal is the Head of the H.GIS and digital cartography division in the Egyptian Hydrographic office. He is a CAT A hydrographer and has 10 years experience in hydrographic field work and data processing. He took over the responsibility of the Digital cartography division and ENC production in parallel with hydrographic work since 2004. He holds a PhD degree from the Arab Academy for Science and Technology and Maritime Transport, Alexandria, Egypt in hydrographic surveying.

Dr. El-Assal is a national expert on the law of the sea and has published several papers in the fields of Hydrographic surveying and digital cartography.

Prof. Dr. Saad M. Abdelrahman is currently the Dean of Education Affairs and Scientific Research in Arab Academy for Science and Technology and Maritime Transport, Alexandria, Egypt. He joined Nautical Department, College of Maritime Transport and Technology as a professor of Physical Oceanography, since 1998. He worked in Faculty of Marine Science, King Abdulaziz University (KAAU), Saudi Arabia from 1989 until 1998 during which he was appointed as a chairman of Marine Physics department. In U.S.A., he worked as an adjunct research professor at Naval Postgraduate School (NPGS), CA during (1986-1987). He joined the Civil Engineering Department, faculty of Engineering, Alexandria University as a lecturer (part time) and also the Institute of Coastal Research in Alexandria as a visiting researcher from 1987 to 1989.

He received his M. Sc. and Ph.D. degrees in 1983 and 1986 from the Naval Postgraduate School (NPGS), California, U.S.A. in Oceanography, with emphasis on coastal processes. In 1980, he received a diploma from NAVOCEANO, U.S.A. in Hydrographic Surveying and Coastal Oceanography. He earned B. Sc. in Civil Engineering, Alexandria University, Egypt in 1973.

Dr.Abdelrahman has specialized in hydrodynamics, coastal processes Oceanography and hydrographic surveying.

Prof. Ahmed El-Rabbany's obtained his Ph.D. degree in GPS from the Department of Geodesy and Geomatics Engineering, University of New Brunswick, Canada. He is currently a full professor and Graduate Program Director at Ryerson University, Toronto, Canada. He also holds an Honorary Research Associate position at the Department of Geodesy and Geomatics Engineering, University of New Brunswick. Prof. El-Rabbany's areas of expertise include satellite positioning and navigation, integrated navigation systems, and hydrographic surveying. He authored an easy-to-read GPS book, which received a 5-star rating on the Amazon website and was listed as a bestselling GPS book. He also published and presented over 180 journal and conference papers and presentations. Prof. El-Rabbany received a number of awards in recognition of his academic achievements, including three merit awards from Ryerson University.