# Artificial Neural Network for Precise Satellite Altimetry Sea Levels Estimations: Testing Using Simulated Data

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# ARTIFICIAL NEURAL NETWORK FOR PRECISE SATELLITE ALTIMETRYSEALEVELSESTIMATIONS:TESTINGUSINGSIMULATED DATA

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**KEY WORDS:** Coastal Altimetry, Deep learning, Neural Network, Coastal Sea Level, Waveform Retracking

**ABSTRACT:**

This paper reports the finding of deep learning technique based on artificial neural network to improve the precision of altimetric sea levels over coastal oceans. It is well-known that waveform retracking protocol is necessary to optimise the estim ated geo p h y s ical parameters. In practise, most of the waveform retracking algorithms are specialised for a particular waveform shape (e.g. multi-peak, ocean-like and quasi-specular). In attempting to generate accurate sea levels from multiple retracking algorithms, one should be concerned about the issue of the existence of relative offset between retrackers that generate 'a leap' in the profiles of th e s ea lev el, thus resulting in inaccurate estimate of the sea level. In this study, the neural network technique is explored to minim is e th e o f f s et values between retrackers. The performance of neural network technique is accessed based on 10,000 simulated data, which are generated using Monte Carlo simulation. The simulated data are produced by considering different physical characteristics of altimetric waveforms and sea states (e.g. wave height). The multi-layer feed-forward neural network with varying param eters ( i. e. number of hidden layers, transfer functions in hidden and output layers, and training algorithm) is explored. There are two s ets o f experiment being conducted. Set 1 considers only 1 input parameter (sea surface height (SSH)), and Set 2 considers 2 input parameters (SSH and significant wave height (SWH)). The findings indicate that the best parameters for offset reduction are n eu ral network Set 2 with 10 hidden layers, in which the lowest root mean square error (0.7 cm) and standard variance deviation ( 0 . 2 cm ) are shown.

## I. INTRODUCTION

When using satellite altimetry data over coastal ocean, it is a standard practice to implement data post-processing technique called as ‘waveform retracking’. It is a protocol to optimize th e estimation of ocean parameters such as sea level, significant wave height and wind speed (Gommenginger et al., 2011).

Over coastal ocean, altimetric waveforms are highly complicated due to interactions among both lands and oceans . In addition, complicated coastal sea states also contribute to th e complexity of waveform shapes. Due to the fact that most of retracking algorithms are specialized for certain shape of waveforms, combining different retracking algorithms (Berry et al., 1998; Idris et al., 2017b; Idris et al., 2017b; Idris and Den g, 2012; Deng and Featherstone, 2006) are crucial when attempting to produce accurate sea levels over coastal oceans. Berry et al., (1998) and Idris et al., (2017b) proposes an ex p ert system to choose the optimal retracker for various waveform shapes, leading to a systematic strategy for decision making. Idris et al. (2017b) combines several retracking algorithms including Ocean Model (Deng and Featherstone, 2006), Modified Threshold (Lee et al., 2010) and Sub-waveform (Idris and Deng, 2012) to retracked altimetric waveforms. The decision to choose the optimal retracker is based on fuzzy inference system (Idris et al., 2017b; Idris and Deng, 2013; Idris, 2014; Idris and Deng, 2012b). Idris et al (2017b), Idris and Deng (2013), and Idris (2014), that also embed the neural network technique to handle the issue of offset when combining different retracking algorithm.

Study by Idris (2014), and Idris and Masrol (2018) reported that the offset among retrackers exist. For instance, offset among the Ocean Model and Modified Threshold retracker is about 2 0 - 30 cm, and 26-36 cm among the Ocean Model and Sub-wavefo rm retracker (Gommenginger et al., 2011). Therefore, when combining the retracked sea levels from various retrackers, o n e cannot simply switch from one retracker to another. In doing so, the retracked sea level profiles become imprecise because of the ‘jump’ in the sea level profiles. Study by Idris (2014) rep o r ted that the value of offset varies due to the variation of significan t wave height (SWH).

This paper further investigates the potential of deep learning technique using neural network approach for reducing the valu e of offset among various retrackers, aiming at producing accurate sea surface height (SSH) data. Neural network has a great potential for reducing the offset value because of its capability of finding the relationship among retracked sea levels. Multi-Layer Feed-Forward (MLF) neural network is adapted in this study (Demuth and Beale, 2006; Howard et al., 2006). The parameters of sea level and SWH are simulated using the Monte Carlo simulation. Through the neural network , the relationship among the varying sea level and SWH is explored, and seamless transition of sea levels is produced. Note that previous study by Idris and Deng (2012a) indicate that there is linear relationship among SLA and SWH.

## II. DATA AND METHODOLOGY

This section describes the data and methodology of the study.

### A. *Simulated Data*

Monte Carlo simulation technique is used to create 10,000 waveform data. The simulated waveforms consider various ocean sea states (Table 1) including varying SWH (0 -4 m), an d tracking gate (bin 30-31). The value of thermal noise, amplitude and slope of trailing edge are fixed as constant.

Table 1. The parameters for simulating altimetric waveforms

| Parameters | Value (unit) |
|---|---|
| Thermal noise | 0.5 |
| Amplitude | 100 |
| Epoch | 30 - 31 bin |
| Significant wave height | 0 - 4 m |
| Slope of trailing edge | 0.02 |
| Tracker range | 40460.5618 m |
| Orbital height | 40533.0266 m |
| Total atmospheric and geophysical corrections | -1.6403 |

The simulated waveforms are retracked using two retracking algorithms: 1) Ocean Model (Deng and Featherstone, 2006), and 2) Modified Threshold 30% (Lee et al., 2010). Th e o u tp u t retracked range from both retrackers are then used to compute retracked SSH, namely 1) SSH Ocean and 2) SSH Threshold 30. When computing the value of SSH, the parameters of orbital height, tracker range and corrections are made constant. The retracked sea levels using Ocean Model is used as a reference when analysing the accuracy assessment.

*B. Development of Neural Network*

MLF neural network trained by back-propagation learning algorithm and supervised by learning method (Howard et al. 2006) is applied. The neural network consists of input layer, hidden layer and output layer. Neural network is performed in two modes of operations, which are training and predictio n . In the training mode, the network is trained by modifying their weight parameters for the best desired function approximatio n. This is done by fed the network with the input and targeted output. In the prediction mode, the network is fed by the in p u t, and the trained network (during the training mode) is implemented to predict the output.

In this study, the simulated data (10,000) are divided in to two : 1) 40% of data are used in training mode; and 2) 60% of data are fed in the prediction mode. During the training mode, the input layers are SSH Threshold 30 (and SWH, for Set 2), and the output layer is SSH Ocean. The neural network is trained. During the prediction mode, the input layers are SSH Threshold 30 (and SWH, for Set 2). Using the trained network, the o u tp u t layer is predicted. The predicted output is the de-offset SSH.

*C. Testing with Neural Network*

The testing with neural network is conducted by fixing the transfer function in hidden (i.e. Logsig) and output (i.e. Purelin ) layers, and training algorithm (i.e. Levenberg-Marquardt). The number of hidden layers is varied between 1 to 10, and the number of inputs is varied between 1 (i.e. Set 1) and 2 ( i. e. Set 2). Table 2 summarised the various algorithms considered in this study.

The performance of the neural networks is examined by computing the root mean square error (RMSE) and standard deviation of difference. The SSH Ocean is used as a reference because it is the standard retracker that is widely used over open oceans. For comparison, the analysis of neural network is compared with the Mean Method (MM). This statistical technique is a common method by several researchers (Berry et al., 1998; Idris et al., 2017b; Idris et al., 2017; Idris an d Den g, 2012; Deng and Featherstone, 2006). It is conducted by computing the mean of difference among retrackers that are computed based on data over open ocean. The mean differen ce is then used to remove the offset value in the retracked SSH over both coastal and open oceans.

Table 2. Two sets of testing with varying number of inputs, transfer function in hidden and output layers, and training algorithm. For each set, the number of hidden layers varied from 1-10

| Set | Transfer function in hidden Layer | Transfer function in output Layer | Training algorithm | Input(s) |
|---|---|---|---|---|
| 1 | Logsig | Purelin | Levenberg-Marquardt (trainlm) | 1 Input (SSH with 30% threshold) |
| 2 | Logsig | Purelin | Levenberg-Marquardt (trainlm) | 2 Input (SSH with 30% threshold and SWH) |

## III. RESULTS AND ANALYSIS

Tables 3 and 4 (and Figure 1) show the performance of neural networks. The experiment using one input layer (without SWH, Table 3) indicates that the RMSE and STD of neural network is 10-11 cm and 8-9 cm, respectively. When compared with the MM, the values of RMSE and STD are much higher; 19. 9 6 cm and 17.42, respectively, suggesting that the MM is inaccurate.

Table 3. Set number 1 with 1 input. Comparison with Mean Method is also shown. The best hidden layer shown in bold showing the most appropriate neural network algorithm

| No of Hidden layer | Set 1 with 1 Input | | | |
|---|---|---|---|---|
| | RMSE using NN (cm) | STD using NN (cm) | RMSE using MM (cm) | STD using MM (cm) |
| 1 | 10.8 | 9.0 | 19.96 | 17.42 |
| **2** | **10.4** | **8.5** | | |
| **3** | **10.4** | **8.5** | | |
| 4 | 10.4 | 8.6 | | |
| **5** | **10.4** | **8.5** | | |
| **6** | **10.4** | **8.5** | | |
| 7 | 10.5 | 8.6 | | |
| 8 | 10.5 | 8.6 | | |
| **9** | **10.4** | **8.5** | | |
| 10 | 10.5 | 8.6 | | |

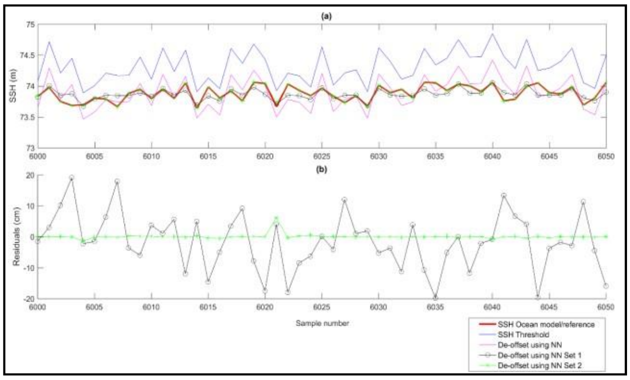


Figure 1. (a) Set 1 (1 input) hidden layer 9 and Set 2 (2 inputs) hidden layer 10 are compared with SSH ocean model to obtain residuals. (b) Residuals value in cm for Set 1 and Set 2

However, significant improvements are seen in terms of the RMSE and STD when the SWH parameter is considered in the neural network for offset reduction (Table 4). By maintaining the similar algorithms of neural network (as in Set 1) but addin g the extra input parameter of SWH, hereafter called as "Set 2", the RMSE and STD are significantly improved to 0.7 cm and 0.2 cm, respectively. Figure 2 illustrates the finding from Set 2.

Table 4. Set number 2 with 2 input. Comparison with Mean Method is also shown. The best hidden layer shown in bold showing the most appropriate neural network algorithm

| No of Hidden layer | Set 2 with 2 Inputs | | | |
|---|---|---|---|---|
| | RMSE using NN (cm) | STD using NN (cm) | RMSE using MM (cm) | STD using MM (cm) |
| 1 | 2.3 | 1.6 | 19.96 | 17.42 |
| 2 | 1.3 | 0.9 | | |
| 3 | 1.2 | 0.7 | | |
| 4 | 1.3 | 0.9 | | |
| 5 | 0.9 | 0.5 | | |
| 6 | 0.9 | 0.4 | | |
| 7 | 0.8 | 0.4 | | |
| 8 | 0.9 | 0.5 | | |
| 9 | 0.7 | 0.3 | | |
| **10** | **0.7** | **0.2** | | |

The relationship among offset and SWH are almost linear (Figure 3). This indicates that the value of offset increases with the increasing of SWH value. The finding in Figure 3 proves that the offset value is not a constant and cannot be simply removed using the MM. Therefore, considering SWH when handling the offset among retrackers are crucial.

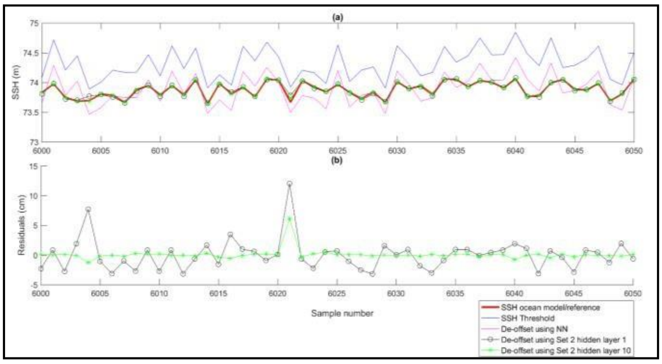


Figure 2. (a) Set 2 hidden layer 1 (worst RMSE) and Set 2 hidden layer 10 (best RMSE) are compared with SSH ocean model to obtain residuals. (b) Residuals value in cm for Set 2 hidden layer 1 and Set 2 hidden layer 10

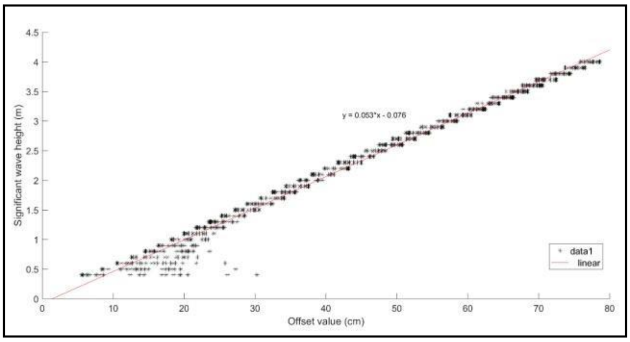


Figure 3. Relationship of offset value (cm) and SWH (m)

## IV. DISCUSSION AND CONCLUSION

The finding from this study is similar to those from Id r is et al. (2017b), and Idris and Deng (2012a) where the variation of offset among retrackers is a variable, not a constant. Th e v alu e of offset varies with varying SWH, suggesting the common MM to minimise the offset is impractical.

This study found that Set 2 (hidden layer 10) is the best algorithms to minimise the offset among the retrackers of Ocean Model and Modified Threshold 30%. This result is nearly similar to that of finding from Idris and Masrol (2018) where they also found the best transfer functions are the Logsig (in hidden layer) and Tansig (output layer). However, the best number of hidden layers is 6, instead of 10 (from this study). Idris and Masrol (2018) reported that the RMSE and STD is 0 . 7 cm and 4.8 cm, respectively, meanwhile this study found the RMSE and STD of 0.7 cm and 0.2 cm, respectively. This indicates improvement in terms of STD using the developed technique in this study. Note that study by (Idris and Masrol, 2018) did not consider any physical variations in the simu lated data, and the simulated SSH is not based on any retracking algorithms. They were created arbitrarily, thus less accurate.

Research is currently on-going to test the neural network algorithms with the real altimetric data and validate the results with independent in-situ data.

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