Seamless transition of altimetric retracked sea levels using neural network technique: case study using simulated data

Nurul Hazrina Idris1,2* and Nurzariyatul Syahirah Masrol1

1Department of Geoinformation, Faculty of Geoinformation and Real Estate, UniversitiTeknologi Malaysia81310, Johor Bahru, Malaysia
2Geoscience and Digital Earth Centre, Research Institute for Sustainability and Environment, UniversitiTeknologi Malaysia, 81310, Johor Bahru, Malaysia

nurulhazrina@utm.my

Abstract. Waveform retracking has become a standard data processing protocol to optimize the estimation of sea level, particularly over coastal oceans. In the proximity of land, combining different retracking algorithms are essential for dealing with high diversity of altimetric waveform patterns. However, retrackers cannot be simply switched to another due to the existence of offset among retrackers. The existence of offset value creates ‘a jump’ in the sea level profiles, thus reducing the precision of the estimated sea level parameter. In this paper, neural network technique is explored to reduce the offset values, and to produce a seamless transition of sea level when switching retrackers. The analysis is conducted over 100,000 simulated data based on Monte Carlo simulation. The experiment includes six sets of varying parameters (i.e. number of hidden layer, algorithms in hidden and output layers, and training algorithm). The results indicate that the neural network (set 2) with six hidden layers, algorithms of Logsig and Tansig for hidden and output layers, respectively, and Levenberg-Marquardt for training algorithm is the best parameters for offset reduction. It has the highest correlation, and the lowest root mean square error and standard deviation of difference, giving it the best rank when compared to the other five sets.

1. Introduction
Waveform retracking is a standard data post-processing protocol to optimize the ocean parameters such as sea level [1]. Since there are no universal retracker (except theAdaptive Leading Edge Subwaveform of ALES [2]) that can deal with the various waveform shapes over the coast, combining different retracking algorithms are essential when producing sea level profiles [3][4][5]. However, one cannot simply switch from one retracker to another because of the existence of offset value in the retracked sea level anomaly (SLA). The offset creates “jump” in the sea level profiles, thus reducing the precision of estimation.

This paper explores the neural network technique for reducing offset in the retracked sea levels. Neural network is a complex model that relate input and output data. It is a multivariate, non-parametric and learning algorithm [6] that can be used as an alternative approach to link the retracked SLAs from different retrackers [7]. The technique can be potentially used to reduce the offset value because of its capability of analyzing linear or non-linear relationship among the retracked sea level.
Multi-Layer Feed-Forward (MLF) Neural Network is adapted in this study. The parameters of sea level and significant wave height (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 [4] indicate that there are linear relationship among SLA and SWH.

2. Simulated Data
There are 100,000 data simulated using Monte Carlo simulation technique. The simulated data are 1) sea level without offset, 2) sea level with offset, and 3) SWH. The sea level without offset ranges from 0-100 cm. It is used as a reference to compute the correlation, root mean square (RMS) error and standard deviation of difference. The sea level with offset is created by adding the offset value ranging from 0-100 cm to the data sea level without offset. The SWH ranges from 0-8 m covering the various ocean sea states condition.

3. Methodology
3.1. Development of Neural Network
MLF neural network trained by back-propagation learning algorithm and supervised by learning method [8] is applied. The neural network consists of input layer, hidden layer and output layer (Figure 1). In this study, two data are embedded in the input layer. They are the sea level with offset, and SWH. Both data represents the real condition of the altimetric retracked sea level profiles, and the ocean sea states. The sea level without offset is assigned as output layer, as this is our targeted output. Note that the SWH is included in the analysis because our previous study [4] indicated that the offset values on the retracked sea levels is a function of SWH. Since the relationship among the offset and SWH is non-linear, neural network is explored.

Neural network is performed in two modes of operations, which are training and prediction. Training mode is used to present sampled data, both in the input (sea level with offset and SWH) and output layers (sea level without offset), so that the network can be trained by modifying their weight parameters for the best desired function approximation. In our study, 60% of the data are used in the training mode. The prediction mode is the process of applying the trained neural network (from the training mode) for a new sample data to produce estimated output value. In our case, the remaining 40% of the simulated data are embedded in the trained network.

![Figure 1. The structure of a MLF neural network technique [9]](image)

In the architecture of MLF neural network, there are three transfer functions in neuron model which are purelin, logsig and tansig [10].
Purelin is a neural linear function (Figure 2) which acts as transfer function to calculate output layer from its network input. It can be expressed as \( \text{Purelin}(n) = n \), where \( n \) is S-by-Q matrix of net input (column) vectors.

![Figure 2. Purelin Transfer Function](image)

Logsig is a transfer function based on log-sigmoid function Figure 3. It can be expressed as \( \text{Logsig}(n) = \frac{1}{1 + \exp(-n)} \), where \( n \) is S-by-Q matrix of net input (column) vectors.

![Figure 3. Logsig Transfer Function](image)

Tansig is a neural transfer function based on tan-sigmoid transfer function (Figure 4). It can be expressed as \( \text{tansig}(n) = \frac{2}{1 + \exp(-2n)} - 1 \), where \( n \) is S-by-Q matrix of net input (column) vectors.

![Figure 4. Tansig Transfer Function](image)

**3.2. Testing with Neural Network**

The testing is conducted using six sets of varying algorithms (Table 1). For each set, the varying number of hidden layers are from 1 to 10.

To identify the performance of the neural network sets, accuracy assessment is conducted by comparing the results with referenced data (i.e. simulated sea level without offset). The assessment is conducted by computing the standard deviation of difference, root mean square (RMS) error and correlation.
Table 1. Six sets of testing with varying algorithms in hidden layer, output layer and training

| Set | Algorithm in Hidden Layer | Algorithm in Output Layer | Training Algorithm       |
|-----|---------------------------|---------------------------|-------------------------|
| 1   | Logsig                    | Purelin                   | Levenberg-Marquardt (trainlm) |
| 2   | Logsig                    | Tansig                    | Levenberg-Marquardt (trainlm) |
| 3   | Purelin                   | Logsig                    | Levenberg-Marquardt (trainlm) |
| 4   | Purelin                   | Tansig                    | Levenberg-Marquardt (trainlm) |
| 5   | Tansig                    | Logsig                    | Levenberg-Marquardt (trainlm) |
| 6   | Tansig                    | Purelin                   | Levenberg-Marquardt (trainlm) |

A systematic ranking strategy is developed to identify the most appropriate neural network sets. High ranking is given to the low RMS error, low standard deviation of difference, and high correlation. Table 2 indicate the ranking strategy given to the RMS error, standard deviation of difference and correlation.

Table 2. The ranking for standard deviation of difference, correlation and RMS error

| Rank | Standard Deviation of Difference | Correlation | RMS Error |
|------|----------------------------------|-------------|-----------|
| 1    | 4.00 – 4.50                      | 0.95 – 1.00 | 0.00 – 0.50 |
| 2    | 4.50 – 5.00                      | 0.90 – 0.95 | 0.50 – 1.00 |
| 3    | 5.00 – 5.50                      | 0.85 – 0.90 | 1.00 – 1.50 |
| 4    | 5.50 – 6.00                      | 0.80 – 0.85 | 1.50 – 2.00 |
| 5    | 6.00 – 6.50                      | 0.75 – 0.80 | 2.00 – 2.50 |
| 6    | 6.50 – 7.00                      | 0.70 – 0.75 | 2.50 – 3.00 |
| 7    | 7.00 – 7.50                      | 0.65 – 0.70 | 3.00 – 3.50 |
| 8    | 7.50 – 8.00                      | 0.60 – 0.65 | 3.50 – 4.00 |
| 9    | 8.0 – 8.50                       | 0.55 – 0.60 | 4.00 – 4.50 |
| 10   | >8.50                            | <0.55        | >4.50      |

4. Results and Analysis

Tables 3-8 show the accuracy assessment and ranking value of the six sets of algorithms (in Table 1). The best total rank is shown in bold showing the most appropriate neural network algorithm. It is seen that in several sets (i.e., set 1 and set 4), the best total rank belongs to several sets of combination. For instance, in set 1 (Table 3), the best total rank (12) belongs to hidden layers 6 and 9. In set 4 (Table 6), the best total rank (16) belongs to hidden layers 3, 5 and 8. The best total rank is shown in bold.

Table 3. The accuracy assessment and ranking value of set 1 with varying number of hidden layers.

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|----------------------------------------|--------------------|------------|
| 1                   | 4.05 (9)               | 7.58 (8)                               | 1.00 (1)           | 18         |
| 2                   | 4.49 (9)               | 5.15 (3)                               | 0.96 (1)           | 13         |
| 3                   | 4.02 (9)               | 5.30 (3)                               | 0.98 (1)           | 13         |
| 4                   | 4.41 (9)               | 5.16 (3)                               | 0.97 (1)           | 13         |
| 5                   | 4.62 (10)              | 4.95 (2)                               | 0.98 (1)           | 13         |
| 6                   | 3.71 (8)               | 5.09 (3)                               | 0.98 (1)           | 12         |
| 7                   | 4.14 (9)               | 5.33 (3)                               | 0.97 (1)           | 13         |
| 8                   | 4.08 (9)               | 5.13 (3)                               | 0.98 (1)           | 13         |
| 9                   | 3.99 (8)               | 5.14 (3)                               | 0.97 (1)           | 12         |
| 10                  | 4.20 (9)               | 5.29 (3)                               | 0.96 (1)           | 13         |
Table 4. The accuracy assessment and ranking value of set 2 with varying number of hidden layers

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|----------------------------------------|-------------------|------------|
| 1                   | 4.19 (9)               | 7.59 (8)                               | 1.00 (1)          | 18         |
| 2                   | 4.53 (10)              | 5.14 (3)                               | 0.97 (1)          | 14         |
| 3                   | 4.37 (9)               | 5.26 (3)                               | 0.96 (1)          | 13         |
| 4                   | 4.34 (9)               | 5.19 (3)                               | 0.97 (1)          | 13         |
| 5                   | 4.93 (10)              | 5.14 (3)                               | 0.97 (1)          | 14         |
| 6                   | **0.67 (2)**           | **4.79 (2)**                           | **0.91 (1)**      | **5**      |
| 7                   | 0.92 (2)               | 8.54 (10)                              | 0.00 (10)         | 22         |
| 8                   | 4.89 (10)              | 5.21 (3)                               | 0.98 (1)          | 14         |
| 9                   | 6.86 (10)              | 5.74 (4)                               | 0.78 (5)          | 19         |
| 10                  | 0.17 (1)               | 8.54 (10)                              | 0.00 (10)         | 21         |

*The best total rank is shown in bold.

Table 5. The accuracy assessment and ranking value of set 3 with varying number of hidden layers

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|----------------------------------------|-------------------|------------|
| 1                   | 4.91 (10)              | 6.13 (5)                               | 0.99 (1)          | 16         |
| 2                   | 3.97 (8)               | 7.64 (8)                               | 1.00 (1)          | 17         |
| 3                   | 4.78 (10)              | 6.23 (5)                               | 0.99 (1)          | 16         |
| 4                   | **2.49 (5)**           | **8.42 (9)**                           | **0.99 (1)**      | **15**     |
| 5                   | 3.86 (8)               | 7.84 (8)                               | 1.00 (1)          | 17         |
| 6                   | 4.00 (8)               | 7.61 (8)                               | 1.00 (1)          | 17         |
| 7                   | 4.46 (10)              | 6.63 (5)                               | 0.99 (1)          | 16         |
| 8                   | 4.10 (9)               | 7.60 (8)                               | 1.00 (1)          | 18         |
| 9                   | 4.69 (10)              | 6.28 (5)                               | 0.99 (1)          | 16         |
| 10                  | 4.28 (9)               | 7.21 (7)                               | 1.00 (1)          | 17         |

*The best total rank is shown in bold.

Table 6. The accuracy assessment and ranking value of set 4 with varying number of hidden layers

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|----------------------------------------|-------------------|------------|
| 1                   | 3.95 (8)               | 7.65 (8)                               | 1.00 (1)          | 17         |
| 2                   | 3.79 (8)               | 7.66 (8)                               | 1.00 (1)          | 17         |
| 3                   | **4.65 (10)**          | **6.35 (5)**                           | **0.99 (1)**      | **16**     |
| 4                   | 3.84 (8)               | 7.71 (8)                               | 1.00 (1)          | 17         |
| 5                   | **4.58 (10)**          | **6.28 (5)**                           | **0.99 (1)**      | **16**     |
| 6                   | 4.12 (9)               | 7.65 (8)                               | 1.00 (1)          | 18         |
| 7                   | 3.90 (8)               | 7.63 (8)                               | 1.00 (1)          | 17         |
| 8                   | **2.51 (6)**           | **8.40 (9)**                           | **0.99 (1)**      | **16**     |
| 9                   | 4.11 (9)               | 7.60 (8)                               | 1.00 (1)          | 18         |
| 10                  | 4.25 (9)               | 7.56 (8)                               | 1.00 (1)          | 18         |

*The best total rank is shown in bold.
Table 7. The accuracy assessment and ranking value of set 5 with varying number of hidden layers.

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|-----------------------------------------|-------------------|------------|
| 1                   | 3.90 (8)               | 7.62 (8)                                | 1.00 (1)          | 17         |
| 2                   | 4.53 (10)              | 5.08 (3)                                | 0.96 (1)          | 14         |
| 3                   | 4.49 (9)               | 5.56 (4)                                | 0.98 (1)          | 14         |
| 4                   | 4.14 (9)               | 5.23 (3)                                | 0.97 (1)          | 13         |
| 5                   | 0.57 (2)               | 8.54 (10)                               | 0.00 (10)         | 22         |
| 6                   | 4.59 (10)              | 5.28 (3)                                | 0.97 (1)          | 14         |
| 7                   | 4.25 (9)               | 5.02 (3)                                | 0.92 (2)          | 14         |
| 8                   | 5.02 (10)              | 5.23 (3)                                | 0.96 (1)          | 14         |
| 9                   | 4.61 (10)              | 4.88 (2)                                | 0.93 (2)          | 14         |
| 10                  | 3.23 (7)               | 8.61 (10)                               | 0.07 (10)         | 27         |

*The best total rank is shown in bold.

Table 8. The accuracy assessment and ranking value of set 6 with varying number of hidden layers.

| No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|---------------------|------------------------|-----------------------------------------|-------------------|------------|
| 1                   | 4.08 (9)               | 7.64 (8)                                | 1.00 (1)          | 18         |
| 2                   | 4.43 (9)               | 5.17 (3)                                | 0.96 (1)          | 13         |
| 3                   | 4.85 (10)              | 5.12 (3)                                | 0.97 (1)          | 14         |
| 4                   | 2.76 (6)               | 6.25 (5)                                | 0.69 (7)          | 18         |
| 5                   | 4.18 (9)               | 5.28 (3)                                | 0.97 (1)          | 13         |
| 6                   | 4.22 (9)               | 5.09 (3)                                | 0.97 (1)          | 13         |
| 7                   | 4.42 (9)               | 5.35 (3)                                | 0.97 (1)          | 13         |
| 8                   | 3.49 (8)               | 6.12 (5)                                | 0.88 (3)          | 16         |
| 9                   | 2.56 (6)               | 4.82 (2)                                | 0.96 (1)          | 9          |
| 10                  | 4.60 (10)              | 5.15 (3)                                | 0.98 (1)          | 14         |

*The best total rank is shown in bold.

In order to decide the most appropriate neural network algorithm, the summary of the accuracy assessment and ranking for the best total rank (based on results in Table 3-8) is shown in Table 9.

Table 9. Summary of accuracy assessment and ranking value for set 1-6 that have the highest total rank.

| Set of Algorithm | No. of Hidden Layer | RMSE in unit cm (rank) | Standard Deviation of Difference (rank) | Correlation (rank) | Total Rank |
|------------------|---------------------|------------------------|-----------------------------------------|-------------------|------------|
| Set 1            | 6                   | 3.71 (8)               | 5.09 (3)                                | 0.98 (1)          | 12         |
| Set 2            | 6                   | **0.67 (2)**           | **4.79 (2)**                            | **0.91(1)**       | 5          |
| Set 3            | 4                   | 2.49 (5)               | 8.42 (9)                                | 0.99 (1)          | 15         |
| Set 4            | 3                   | 4.65 (10)              | 6.35 (5)                                | 0.99 (1)          | 16         |
| Set 5            | 4                   | 4.14 (9)               | 5.23 (3)                                | 0.97 (1)          | 13         |
| Set 6            | 9                   | 2.56 (6)               | 4.82 (2)                                | 0.96 (1)          | 9          |

*The highest total rank is shown in bold.
It is seen that set 2 with hidden layer 6 has the best total rank of 5. It has the smallest RMS error (0.67 cm) and standard deviation of difference (4.79 cm) when compared to the other sets. Although the value of correlation is slightly lower than those of the other set, it is considered as high exceeding 0.9. Figure 5 shows the SLA profiles after applying the neural network algorithm set 2. It is seen that the profile is well-agreed to those of the referenced SLA without offset, confirming the statistical finding in Table 9.

![Figure 5](image_url)

**Figure 5.** The profiles of SLA with offset (in black), the referenced SLA without offset (in red), the SWH (in cyan). The SLA profiles after applying neural network algorithm set 2 (hidden layer 6) is indicated in blue line (with diamond marker).

5. **Conclusion and Recommendations**

Based on the results, it can be conclude that the neural network algorithm set 2 with hidden layer 6 is the most appropriate algorithm for reducing the offset in the SLAs. Research is currently on-going to test the neural network algorithms with the real satellite altimetric data for producing seamless SLA profiles when combining multiple retracking algorithm. Validation of the technique with independent in-situ data will also be conducted.

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