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Application of the neural network on the GNSS-Reflectometry data for the estimation of the significant wave height

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Abstract

Globally, remote sensing is the best way to estimate Significant Wave Height (SWH). Traditional sensors such as satellite altimeters are generally used to provide SWH. However, due to poor temporal resolution and poor signal quality during heavy rain, altimeters signals are not suitable during heavy rain condition. To overcome above limitations, Global Navigation Satellite System-Reflectometry (GNSS-R) is widely used to generate the ocean parameters. However, due to the poor range resolution of GNSS-R signals, GNSS-R requires complex algorithm to generate SWH. In this paper, a Neural Network (NN) based machine learning technique is proposed to estimate the SWH using Cyclone GNSS (CYGNSS) observables. Levenberg-Marquardt algorithm is applied to train and update the weight function and bias of the network. Optimum number of layers and nodes in each layer are selected by the criteria which minimize the error of the output of the NN. Once the network is formed, the estimated SWH is validated using SWH of WW-3 model. The training data gives the Correlation Coefficients (CC) equals to 0.91 and Root Mean Square Difference (RMSD) equals to 0.35 m. The validation data gives the RMSD and the Mean Error (ME) equals to 0.36 m and -0.002 m respectively. NN output is also compared with Jason-3 altimeter SWH data. The analysis shows that similar to altimeter, GNSS-R signals can also be used to generate SWH.

1. Introduction

The knowledge of the ocean wave plays vital role to understand the ocean dynamics for coastal monitoring [1, 2]. The main parameter to determine the ocean dynamics is the Significant Wave Height (SWH). SWH is generally used as the input in ocean wave forecast models [3]. There are several sensors to measure SWH; using buoy, satellite altimeters etc. [4]. Though buoy measures accurate SWH, the data coverage is limited to its location. For global coverage, the best way to get SWH is through satellite remote sensing. Presently, satellite altimeters data are used to estimate SWH with <0.5 m accuracy [3]. However, SWH from satellite altimeter cannot be used effectively in ocean wave modeling due to its limited spatial and temporal resolution. Also, the attenuation of the altimeter signals during rainy conditions hampers the use of altimeter data during extreme weather conditions [5]. A constellation of the CYclone GNSS (CYGNSS) satellites provides an alternate way to estimate SWH with the high temporal and spatial resolution. Moreover, CYGNSS signals operate at L-band. Due to lower frequency as compared to altimeter, the attenuation in the CYGNSS signal during rain is negligible as compared to altimeter signal [6, 7]. Global Navigation Satellite System-Reflectometry (GNSS-R) signals are widely used for various ocean remote sensing applications such as ocean surface wind. However, limited research is available in the direction of GNSS-R derived SWH [1, 2]. Traditional approach to derive SWH is by using waveform data. It is considered that due to the poor range resolution of GNSS-R signals as compared to altimeter, GNSS-R cannot provide the SWH as accurate as provided by the altimeters using waveform data. Therefore, to achieve the accuracy similar to altimeter, complex algorithms such as machine learning can be applied.

In this paper, an attempt is made to estimate SWH using Neural network (NN) based machine learning technique with CYGNSS data. The paper is arranged in five sections: section 2 describes the data used in this paper. Section 3 gives the detailed description of the NN formation which is followed by discussion about results in section 4. The concluding remark of this work is explained in section 5.

2. Data used

In this paper, NN based machine learning technique is applied to estimate SWH. To establish the network, CYGNSS level 1 data are used as input parameters for NN formation. National Oceanic and Atmospheric Administration (NOAA) Wave Watch -3 (WW-3) SWH data are used to train the network [8]. The input are the normalized values of CYGNSS parameters such as elevation angle, azimuth angle, signal to noise ratio of delay doppler map, normalized bi-static radar cross section, incidence angle, Fresnel reflection coefficient, figure of merit of the receiver corrected gain. Further comparison of the NN output is carried out using Jason-3 altimeter (J3) SWH.

3. Neural Network formation

Different sensors have different spatial and temporal resolution. Therefore, collocation is required to bring them at the common resolution [6]. For collocation, WW-3 data are interpolated in time and space domain by using linear and bi-linear interpolation scheme respectively [2]. Before the collocation, bad quality data points are flagged. In this way, total 2000627 points are used to build the network. .

To form the network, data is divided into training, testing and validation set with ratio of 60:20:20 respectively. The selection of points for training, testing and validation is random. Log sigmoid function is used as transfer function between the layers while Levenberg-Marquardt optimization algorithm is applied to train the network to update the weight function and biases.

Then, the hidden layer selection for NN is carried out by using Eq. 1 [9].

$$h = \sqrt{I + O} + A \qquad \text{Eq. 1}$$

where h is the number of nodes in hidden layer , I and O are the number of nodes in the input and output layer respectively. A is an arbitrary constant which varies from 1 to 10 [9].

4. Results and discussion

The performance of the network with training, testing and validation data is shown in Fig. 1. It is observed that the NN converges rapidly for all the three data sets. The visual inspection of the figure shows that there is no fluctuation in the validation and testing data set over time which confirms the generalization of the network.

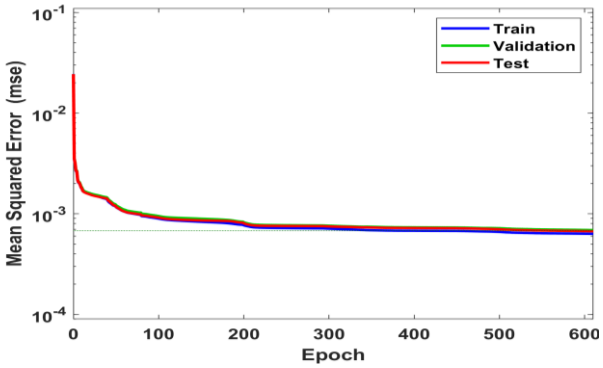

Fig. 1: Training, testing and validation progress in neural network. Y axis is in logarithmic scale.

Fig. 2 represents the density scatterplot between SWH from WW-3 and NN output. The statistics of the comparison of SWH from WW-3 and NN is also shown in the figure in terms of Root Mean Square Difference (RMSD), Mean Error (ME) and Correlation Coefficient (R). The training data gives the RMSD equals to 0.35 m and R equals to 0.91. It has been found that the high density points of SWH are concentrated around the 1:1 agreement line. The ME is near to zero which shows that the SWH from proposed algorithm is matching well with the SWH from WW-3 model. There are few points at which NN derived SWH is higher than the WW-3 SWH. These are the points with high incidence angle and located near to the edge of the CYGNSS coverage area.

Overall, the RMSD and ME with the validation data is equal to 0.36 m and -0.002 m, respectively. Altimeter derived SWH also provides the similar statistics [10].

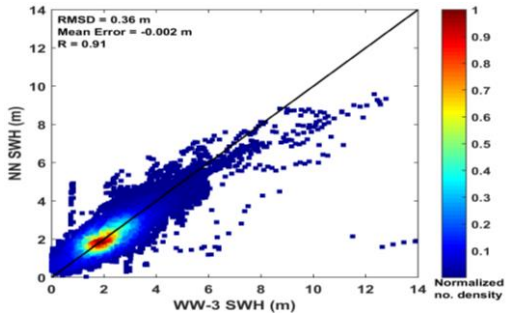

Fig. 2: Density scatter-plot of the SWH from WW-3 model and NN. Black colour line is 1:1 agreement line.

To investigate it in detail, the global variation of SWH using WW-3 and NN is studied. Fig. 3 represents the typical global distribution of the interpolated SWH from WW-3 model at CYGNSS satellite ground tracks for a day. The global mean value of WW-3 SWH is 2.20 meters on 23rd September 2017. The day is selected to capture the high value of SWH due to cyclone Maria in the Atlantic Ocean which is also visible in the figure.

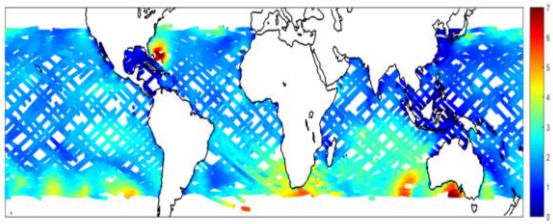

Fig. 3: Global distribution of SWH from WW-3 for 23rd September 2017 at ground track of CYGNSS satellite with spacecraft id 07. Colour bar represents SWH in meter.

The output of the NN based SWH is shown in Fig. 4. It is observed that the global mean value of estimated SWH is 2.15 meters which is matching with the mean value of WW-3l. Similar to Fig. 3, the proposed algorithm is also able to capture high value of SWH along the cyclone Maria track in the Atlantic Ocean.

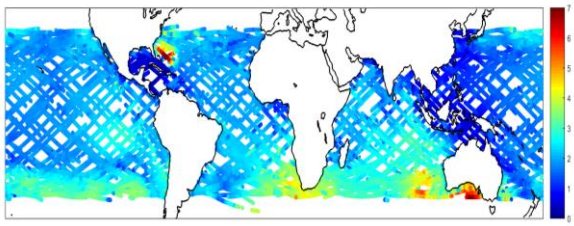

Fig. 4: Global distribution of SWH from NN for 23rd September 2017 at ground track of CYGNSS satellite with spacecraft id 07. Colour bar represents SWH in meter.

Further analysis is carried out by analyzing the difference of SWH using WW-3 and NN is studied. Fig. 4 represents the difference between SWH from NN and WW-3. As shown in the figure, the difference is within ±1 m globally. However, it is higher near the coastal line and at the edge of the coverage area.

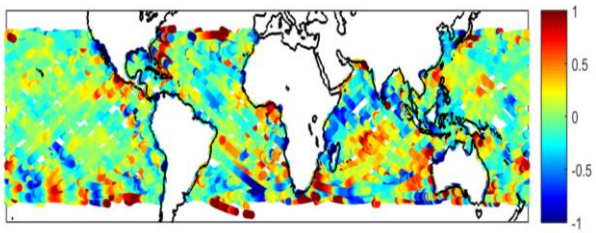

Fig. 5: Global distribution of the difference in SWH between WW-3 model and neural network output for 23rd September 2017 for CYGNSS satellite with spacecraft id 07. Colour bar represents SWH difference in meter.

To compare J3 and NN derived SWH, a spatial window of 25 km and temporal window of 1 hour is considered as collocation criteria. In this way total 113 points are available for the comparison.
The comparison of the SWH from J3 and NN in terms of scatterplot is shown in Fig. 6. It was observed that the points are concentrated around the black line which is 1:1 agreement line. However, few points show negative bias with respect to J3 SWH. It is shown with red circle in the figure. It is similar to the bias which is observed when the SWH from NN is compared with the WW3.

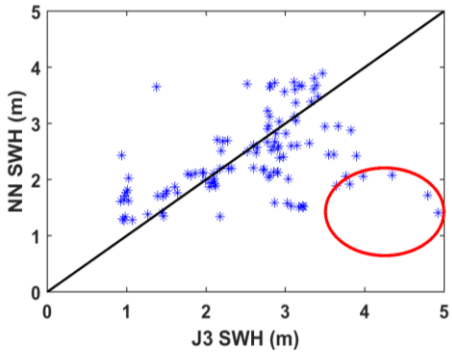

Fig. 6: Scatterplot between Jason-3 SWH and NN derived SWH for 30th April 2019. Red circle represents the points when SWH from NN shows the negative bias with respect to Jason-3 SWH. Black colour line is 1:1 agreement line.

It has been found that the difference is large when incidence angle is high and the points are at the edge of the coverage area. The high incidence angle increases the noise in the signals and reduces the sensitivity of the signals towards the geo-physical parameters [11]. Therefore, the points with incidence angle greater than 40° should not be used for developing the algorithm using CYGNSS. The RMSD reduces to 0.51 m from 0.96 m while the ME decreases to -0.02 m from 0.22 m when these points are excluded from generating the statistics. Overall, NN based SWH estimation technique is found in good agreement with the WW-3 model SWH as well as J3 altimeter SWH. Proposed algorithm is able to meet the accuracy criteria to estimate SWH.

5. Conclusion

In this paper, NN based machine learning algorithm is applied on CYGNSS measurements to estimate SWH.
The density of SWH estimated using proposed algorithm is concentrated around the 1:1 line agreement with the correlation coefficient equals to 0.91. The global mean value of the computed SWH using NN is matching to the WW-3 SWH. The RMSD equals to 0.36 m when NN derived SWH is compared with WW-3 SWH. Similar statistics are mentioned in various literatures when SWH from different satellite altimeter missions are compared [3, 4]. The performance of the proposed algorithm is also compared with the SWH from J3 altimeter. The RMSD value in proposed method is 0.51 m as compared to J3 data. Overall, the estimated SWH is in good agreement with the WW-3 and J3 data. It is shown that the proposed algorithm is capable to produce the SWH using GNSS-R within the required accuracy criteria of altimeter derived SWH.

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