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Multi-Parameter Neural Network for Altimeter Tropical Cyclone Wind Speed Estimation

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Abstract. The ability of satellite altimeter to estimate wind speed in tropical cyclone condition has been investigated. In the extreme condition with higher spatio-temporal variation, the ocean-atmosphere interaction is very complex and makes the existing algorithm become an ill-posed solution. In such condition, the developed algorithm from single frequency backscatter and significant waves height were insufficient. Besides, wind speed estimates become saturated at high regimes and the reflected backscatter was contaminated by rain. Therefore, other simultaneously observed parameters are needed to comprehensively account for this condition and is expected to improve the accuracy of wind speed retrieval. Aside from altimeter instrument, the microwave radiometer onboard Jason-2 concurrently records the brightness temperature and the rain information. To accommodate related multiple parameters for wind speed derivation, the neural network approach is proposed. Its unique advantage is relationship among multi-parameters can be easily established without prior knowledge on their physical attributes. Therefore, this study intended to determine the multi-parameter neural network (MPNN) model in estimating altimeter wind speed during the tropical cyclone condition. The results proved that the MPNN technique has potential in reducing the root mean square error by 30% in comparison between tropical cyclone wind speed estimate by the existing algorithm.

1. Introduction

Measuring near-surface wind speed inside the tropical cyclone is challenging and scientifically important. Studies suggest that the intensity of tropical cyclone has potential to become stronger over consistent warming climate environment [1]. Along with destructive high wind speed, the confluence of storm surges and torrential rain combined had caused severe damage. For instance, Typhoon Haiyan in 2013 was one of the most powerful typhoons ever to make landfall in recorded history. This gigantic typhoon with the diameter of more than 600 km crossed the Philippine archipelago and was responsible for 6300 fatalities, 1061 missing and 28,689 injuries the aftermath [2]. In addition to the huge impact on human, tropical cyclone is one of the complex ocean-atmosphere phenomena in which always becoming an interesting and active research topic. The primary data measurement typically used to monitor this gigantic event is from geostationary operational environmental satellite platforms such as Himawari. Although this observation is operationally accepted, it is limited to cloud-top pattern and the infrared imagery, which can only observe the aerial view of the structure. The top cloud and tropospheric wind information usually used to forecast the tropical cyclone trajectory. In contrast, wind at the 10-meter height from the surface is the utmost parameter needed to estimate the current tropical cyclone strength and intensity and yet, this parameter was not accounted. Perhaps this is one of the main reasons of no significant improvement was established in the forecasted tropical cyclone intensity accuracy over several decades [3].

Despite of the fact that the active microwave polar-orbiting altimeter satellite is known to have small field of view (FOV) and long revisiting time disadvantages, one cannot simply deny their ability to accurately estimate ocean surface wind speed [4],[5]. Unlike scatterometer in which wind speed is not the primary parameter that altimeter dedicated to, many studies have developed algorithms to infer wind speed from the reflected altimetric backscatter [6]. The amplitude of the backscatter energy is closely related to the sea surface roughness which is significantly modulated by the surface gravity waves and the wind force [4],[6],[7]. However, most of the developed algorithm is limited to the normal-to-moderate wind speed regime at a neutral atmospheric stability condition in which, is certainly not the typical ambience during the tropical cyclone event. As reported by many [8], the estimated wind speed is consistently reducing its accuracy and becoming saturated when it reaches speed greater than 18 m/s (34-kt). One of the earliest works on adjusting the empirical fitting for high wind speed region was conducted by Young [9] and resulted reasonable accuracy when comparing with the model. As the studies progress, more scientific explanation about the altimeter signal reacts under an extreme condition or during tropical cyclone were investigated [8],[10].

Although the backscatter signal is the main parameter that shows strong physical and empirical inverse relationship with sea surface roughness and wind speed, other surplus parameters are suggested. The simultaneously recorded parameters such as significant waves height and brightness temperature can be further analysed to improve the accuracy of the estimated wind speed inside the complex ocean-atmosphere tropical cyclone environment. Although Quilfen et al. [8] proposed a new improved wind speed model during high wind condition, they highlighted that one should not ignore the valuable sea state information in extreme seas provided by the altimeter data. In fact, the operational Gourrion 2002 GMF [4] framework exploiting the single frequency Ku-band backscatter and significant wave height to derive the altimeter wind speed. Besides, Quilfen [11] also suggested the dual-frequency approach for higher measurement accuracy than of the single Ku-band frequency, which is strongly affected by rain. However, integrating these multi-parameters into the analytical algorithm is complicated, tedious and ill-posed solution. This is not a case for neural network as its machine learning framework allows to establish relationship networks among multi-parameters without a prior knowledge on their physical attributes. Few researches have implemented the same approach [12], however, limited attention has been focusing on estimating wind speed in tropical cyclone condition.

This paper aims to estimate wind speed inside the tropical cyclone condition using ten parameters simultaneously observed by Jason-2 altimeter. The Jason-2 mission is a project of the common interest between NASA (National Aeronautics and Space Administration), NOAA (National Oceanic and Atmospheric Administration), CNES (Centre National d'Etudes Spatiales) and EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites). The neural network technique established in MATLAB was used to estimate the wind speed from Jason-2 altimeter data during the tropical cyclone condition. This study is anticipated to increase the tropical cyclone wind speed accuracy with the implementation of multi-parameter neural network when compared to the operational geophysical model function.

2. Data and materials

2.1. Jason-2 and Metop-A data

Jason-2 altimeter and Metop-A scatterometer are both active microwave satellites that transmitting their own energy pulses to the target and recording the return backscatters. This study used the Geophysical Data Record (GDR) products of the Jason-2 mission reprocessed by CNES from Archiving, Validation and Interpretation of Satellite Oceanographic Data (AVISO) database. Whereas for scatterometer, Metop-A Ascat Level 2 Ocean Surface Wind Vectors Optimized for Coastal Ocean product was provided by the Physical Oceanography Distributed Active Archive Center (PODAAC). General specification of both missions is listed in Table 1.

Both Jason-2 and Metop-A data were temporally and spatially filtered over 115 tropical cyclone events recorded in Northwest Pacific, Northeast Pacific and North Atlantic regions throughout the year 2015 to 2018. These three regions are the most active regions on earth with tropical cyclone occurrence [13]. Japan Meteorological Agency (JMA) is responsible to monitor all the tropical cyclone activity over Northwest Pacific region while Northwest Pacific and North Atlantic are belonged to United States agencies including National Hurricane Center (NHC), Central Pacific Hurricane Center (CPHC) and Joint Typhoon Warning Centre (JTWC). All these agencies are accountable to report the best track for each tropical cyclone events in their respective regions. Then both Jason-2 and Metop-A data were temporally filtered based on 6-hourly best track report and within the spatial radius of 34-kt average geographical quadrant for Northeast Pacific and North Atlantic and radius of maximum 30-kt for Northwest Pacific from the tropical cyclone centre.

Table 1. General satellite specifications of Jason-2 altimeter and Metop-A scatterometer.

Specifications	Jason-2	Metop-A
Global Coverage (day)	10	1.5
Spatial Resolution (km)	25	<5
Swath (km)	30	1100

2.2. Jason-2 Parameters

This study tends to exploit the simultaneously observed surplus parameter in improving the accuracy of the wind speed estimate during the tropical cyclone condition. There are several payloads attached on the Jason-2 platform such as Poseidon-3 altimeter and Advance Microwave Radiometer (AMR). Poseidon-3 altimeter operates in two frequencies - 5.3 GHz C-band and 13.58 GHz Ku-band. The unbiased backscatter coefficient of C-band (sig0c) and Ku-band (sig0ku) were corrected using atmospheric correction of each respective frequency. Besides the backscatter, significant waves height at C-band (swhc) and Ku-band (swhku) were used as the parameters to estimate wind speed. The last parameter of Poseidon-3 is the sea surface height anomaly (ssha) which was derived from higher accuracy of Ku-band measurement. On the other hand, the AMR provides the brightness temperature at 18.7 GHz (tb18), 23.8 GHz (tb23) and 34.0 GHz (tb34). Water vapour content (wvc) and liquid water content (lwc) are other parameters derived from AMR payload. This study takes into account all ten parameters from Jason-2 because of either one can affect the measurements from altimeter through atmospheric attenuation or affected by the wind speed itself as suggested by others [4],[11],[12].

3. Methodology

3.1. Spatial and temporal match-up data

Much attention has been focusing on improving scatterometer ocean wind field estimation especially at speed above 15 m/s [5],[14]. Scatterometer product is widely accepted wind speed information for JMA and NHC operationally, and the altimeter points collocated to scatterometer pixel is considered adequately match-up at time and space. This study chooses to find the collocated Jason-2 to Metop-A to yield correlated match-up inside the tropical cyclone. Fig. 1a shows the example of match-up during a crossing Jason-2 track with Metop-A within the radius of 30-kt wind speed over mature and stable typhoon in the Northwest Pacific region.

When both satellites are crossing, the distance between observations must be within the spatial distance of less than 0.25° as further illustrated in Fig. 1(b) for a single altimeter point. The spatial is in agreement with [4],[8]. However, this study tends to impose a harsher temporal interval which is ± 30 minutes. Despite spatially averaging the whole match-up point-based scatterometer parameters, this study only accepts scatterometer points with the closest distance to altimeter point. The goal of having a shorter time gap and closest distance criteria is to preserve higher spatial and temporal resolution of both data points inside the tropical cyclone structure. Match-up of 7553 points was found throughout the whole 115 tropical cyclone events. To ensure only quality is used, this study only accepts quality backscatters, significant wave height and brightness temperature data flags. Also, the match-up was screening for open-ocean state and non-contiminated rain state only. Finally, high quality data of 5791 match-up points were extracted.

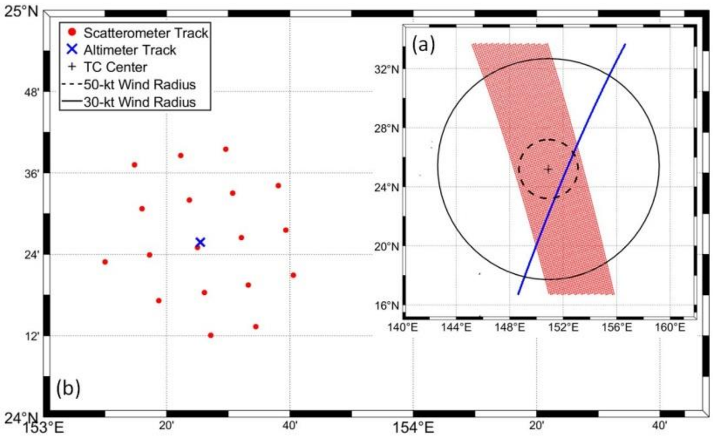

Figure 1. Data match-up between Jason-2 and Metop-A observation as both satellites crossing tropical cyclone event in (a). A closer look of 1x1° grid into a single Jason-2 point in blue cross with multiple Metop-A points at centre of pixels in red dots depicted in (b).

3.2. Multi-Parameter Neural Network

Many studies consistently show that conventional geophysical model function (GMF) algorithms are not straighforward in deriving tropical cyclone wind speed [8],[15]. This caused by the lack of physical understanding when the air-sea interactions are fierce and the general physical relation of the wind-driven ocean GMF is becoming an ill-posed solution. However, to develop a multi-parameter regression method is tedious and demands a comprehensive understanding on physical relationship among parameters. It has been demonstrated in some studies that artificial neural network (ANN)-based estimation gives better accuracy and is more practical than those estimated using multiple regression techniques [16],[17]. The multi-parameter neural network (MPNN) was chosen to estimate the wind speed in extreme condition considering that this technique can overlook the complex physical interaction inside the tropical cyclone.
Among those 5791 high quality match-up points, 60% of the samples were chosen for a training dataset, while the rest of 40% were used for validation. As illustrates in Fig. 2, 10 selected parameters (namely as sig0c, sig0ku, swhc, swhku, ssha, tb18, tb23, tb34, wvc, and lwc) were assigned at input layers and connected to the desigated networks. During the forward phase, input parameters were connecting to the hidden layers that contain 15 neurons. It was then propagated to the output layers for estimating altimeter wind speed. Metop-A scatterometer wind speed act as a targeted output was used to calculate the error of the estimated altimeter wind speed. The error was reused to propagate back in backward phase and adjusting the sequential weight and bias for each connecting neurons. Bayesian regularization technique was chosen as the training algorithm due to its capability in handling complex relationship among ten parameters at the robust fashion [18]. One epoch defines complete estimation cycle in both forward and backward phases. The final epoch terminates the processing when the error has reached the minimum to determine the estimated altimeter wind speed. All corresponding deliverable statistics and numerical were reported and later used for the analysis.

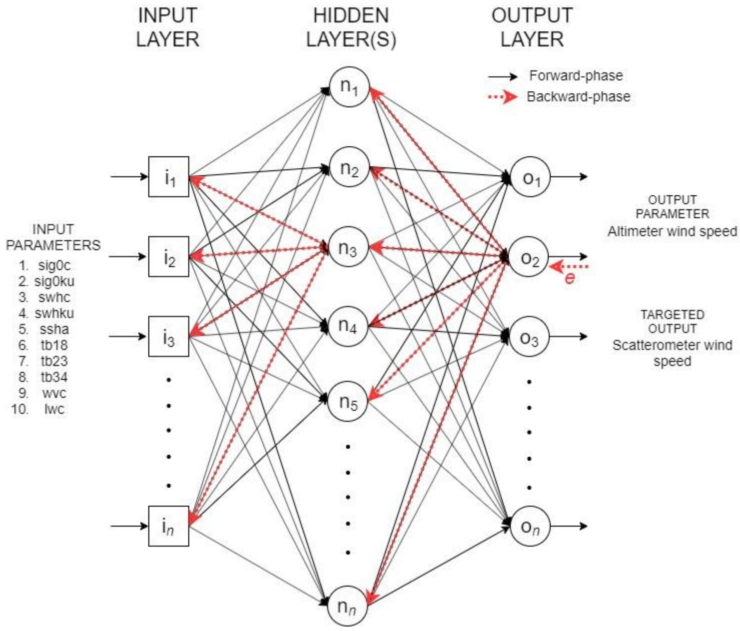

Figure 2. The processing architecture of the neural network of forward- and backward-phase. The i_1 to i_n is the number of match-up data used in training (in this case, 60% of the samples) which resulted in the o_1 to o_n output of the wind speed estimate. The n_1 to n_n is the number of processing neurons assigned to the corresponding hidden layers.

4. Results and discussions

4.1. Validation

To test the accuracy of the MPNN, the established network should be tested with data which were not used during the training and thus, the remaining 40% of the data was used. Figure 3(a) and (b) presents the scatter plot of wind speed estimate from the raw altimeter Jason-2 using operational GMF Gourrion 2002 and the derived MPNN to the scatterometer Metop-A wind speed product respectively. The point density between GMF- and the scatterometer-derived wind speed is more sparsely distributed than of the MPNN. Wind speed of MPNN shows excellent agreement to the best linear fitting and there is slight deviation in the case of GMF derived data. Estimation improvement can be seen starting at the ranges of 10 m/s and become significant as it levels to 15 m/s and above. The result shows that the GMF has begun to be saturated at the speed of 18 m/s and above that slightly deviates the fitting line away from its best fit one. Unlike GMF, the wind speed estimate of MPNN can be derived at this range. Although the R-square improvement is just around 4% (Gourrion 2002=0.9424, MPNN=0.9749), but the RMSE is significantly improve for more than 30% (Gourrion 2002=0.947 ms-1, MPNN=0.644 ms-1).
To refine such result, the box-whisker plot was used to quantitatively demonstrate the numerical deviation between GMF- and MPNN-derived wind speed which is shown in Figure 4. The overall median line position of the box-whisker plot has indicated that Gourrion 2002 (Fig. 4a) underestimates wind speed in tropical cyclone condition as low as 5 ms-1. In fact, their data distribution has more expension beyond the 95% confidence threshold which is evident by the red cross marker distribution. Although the median line of MPNN (Fig. 4b) has a closer agreement with the Metop-A wind speed, both data have underestimated high wind speed starting at the range of 17 ms-1. The short interquartile range of MPNN data presents that the neural network technique provided more consistent estimation (with lower quartile deviation) with Metop-A wind speed in tropical cyclone condition.

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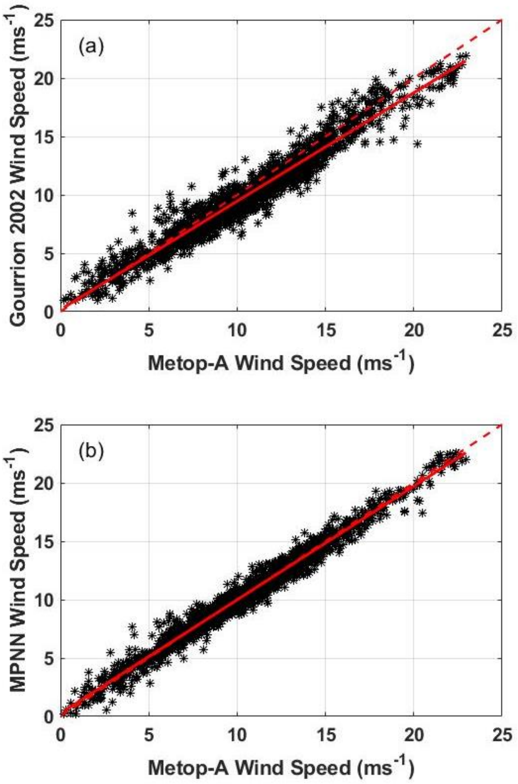

Figure 3. The scatter plot of the wind speed estimates using the raw Jason-2 as a function of Gourrion 2002 model (a) and the MPNN (b). Black asterisk shows the match-up points, red solid-line is the estimated linear fitting, and red dashed-line is the best fit.

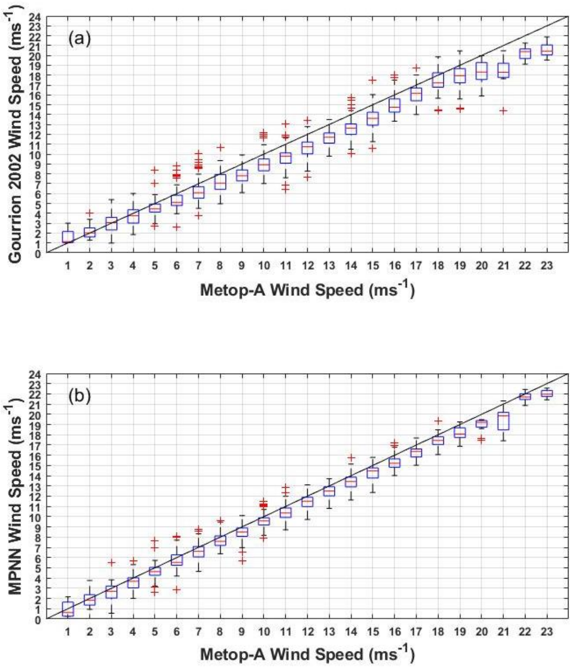

Figure 4. Box-whisker plot of the Gourrion 2002 (a) and MPNN (b) estimated wind speed against Metop-A.

4.2. Tropical cyclone event

Further validation beyond the use of scatterometer throughout the altimeter track is very difficult and visual comparison is exclusive for any specific tropical cyclone event. For visual comparison, validation during a Typhoon Jebi on 29 August 2018 over the Northwest Pacific Ocean is exclusively presented. Typhoon Jebi match-up was intentionally excluded from the training and validation dataset previously mentioned. This is to assess the agreement achieved by MPNN in real tropical cyclone event. Jason-2 at 10:36 a.m. local time, while Metop-A crossing the same typhoon four minutes later in the northwest direction as shown in Fig. 5a.

The Fig. 5b shows that Jason-2 MPNN and Metop-A wind speed are in good resemblance despite there is very little time different. A remarkable result is the agreement of the maximum wind speed estimation of both sensors at the region of very high wind speed close to the tropical cyclone's eye, marked in blue arterisk. The MPNN has successfully estimates wind speed at the region of more than 25 ms-1 which is comparable to the Metop-A estimates. The shape of the MPNN tropical cyclone wind structure is almost identical in calm condition with low wind speed regime (below 15 ms-1) and has fairly similar pattern with the Metop-A in the extreme regime. This information can be vital for tropical cyclone warning centres such as JMA and NHC, especially when scatterometer observation is absent. For instance, JMA practice the standard of 50-kt and a 30-kt threshold for tropical cyclone strength (where 1-kt = 0.5144 m/s) in which it can be identified from 17° latitude crossing Typhoon Jebi stretch out to 19° in a northeast direction.

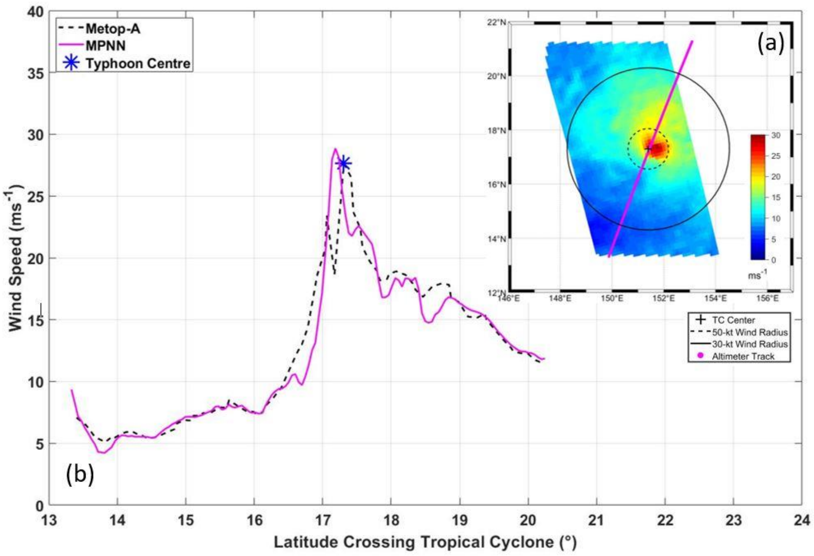

Figure 5. Typhoon Jebi wind radius from the JMA best track report on 29 August 2018 at 12:00 with Metop-A wind speed map and Jason-2 crossing track are shown in (a). The profile of wind speed derived from MPNN and Metop-A match-up is shown in (b) represents the tropical cyclone wind structure.

5. Conclusion and recommendation

This preliminary study reaffirms the ability of satellite altimeter in estimating tropical cyclone wind speed by exploiting simultaneously observed multi-parameters with the implementation of neural network technique. The proposed neural network technique can overlook the complex multi-parameter relationships in the tropical cyclone complex environment by providing relatively more accurate wind speed such as from scatterometer data. All the input used to train the network is either can affect the altimeter measurement through atmospheric attenuation or having a direct impact on wind speed over the ocean surface. By exploiting the unique advantage of neural network technique, further study can enhance the target output with higher accuracy tropical cyclone wind speed data. A comprehensive study on parameter analysis in estimating altimeter wind speed should be conducted. Fully aware that the Gourrion 2002 GMF is operationally recognised in calm and normal condition, the proposed MPNN technique is suggested to have more advantage in the tropical cyclone condition and able to resolve its wind speed threshold strength. Such good agreement measurement with the scatterometer, despite its narrow swath coverage, can be a vital complement to the sea surface wind speed observation in monitoring tropical cyclone event. The advantage of having greater along-track spatial resolution can be further examined for their ability to resolve the finer detail structure of tropical cyclone.

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