Passive Microwave Remote Sensing for Sea Ice Thickness Retrieval Using Neural Network and Genetic Algorithm

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Abstract— Over the years, global warming has gained much attention from the global community. The fact that the sea ice plays an important role and has significant effects towards the global climate has prompted scientists to conduct various researches on the sea ice in the Polar Regions. One of the important parameters being studied is the sea ice thickness as it is a direct key indication towards the climate change. However, to conduct studies on the sea ice scientists are often facing with tough challenges due to the unfavorable harsh weather conditions and the remoteness of the Polar Regions. Thus, microwave remote sensing offers an attractive mean for the observation and monitoring of the changes of sea ice in the Polar Regions for the scientists. In this paper, we will be presenting 2 approaches using passive microwave remote sensing to retrieve sea ice thickness. The first approach involves the training and testing of the neural network (NN) by using data sets generated from the Radiative Transfer Theory with Dense Medium Phase and Amplitude Correction Theory (RT-DMPACT) forward scattering model. Once training is completed, the inversion for sea ice thickness could be done speedily. The second approach utilizes a genetic algorithm (GA) which would perform a search routine to identify possible solutions in sea ice thickness that would match the corresponding brightness temperatures profile of the sea ice. The results obtained from both approaches are presented and tested by using Special Scanning Microwave Imager (SSM/I) data with the aid of the sea ice measurements in the Arctic sea.

1. INTRODUCTION

In order to understand the interactions between the wave and sea ice medium, a forward scattering model based on Radiative Transfer Theory was constructed. This forward scattering model was further improved by incorporating Dense Medium Phase and Amplitude Correction Theory (RT-DMPACT) to take into account of the effect of the closely placed scatterers in the sea ice medium. This forward scattering model formed the basis of our inverse model for the sea ice thickness retrieval process. For the NN approach, multiple pairs of data set consist of different sea ice parameters and thicknesses with the corresponding brightness temperatures are first generated using the forward scattering model. This data set will be provided to the NN to create a range of sea ice thickness profile to be used for NN training. The training process is completed when the error generated by NN is acceptably small. After that, inversion is done by providing the brightness temperature profiles of the sea ice to obtain the corresponding sea ice thicknesses. As for GA, a pool of chromosomes representing sea ice thicknesses is created to be fed into the forward scattering model. The chromosomes are then evolved and carried forward to the next generation according to the natural selection concept, whereby the fittest candidate is more likely to survive and to reproduce. The generation and creation continues until the one of the chromosomes has been found to be suitable to be the thickness solution for a given brightness temperature profile.

2. DATA TRAINING AND SEA ICE THICKNESS INVERSION BY NN

The RT-DMPACT Model mentioned above is used to calculate the passive microwave returns in terms of brightness temperatures of vertically (T_{Bv}) and horizontally (T_{Bh}) polarized wave. The Neural Network (NN) constructed consists of an input layer, two hidden layers and an output layer. Each layer employs several neurons, which are connected to other neurons in the adjacent layer with different weights. The signals propagate from input layer, through hidden layers and to the output. The network is trained by the input-output data generated from the RT-DMPACT Model. The training process is carried out by changing the values of the interconnecting weights of the neurons in the layers by using Levenberg-Marquardt Algorithm (Martin H. & Mohammad B. M. 1994), according to the error generated. The weights in the NN are then changed in each iteration to reduce the error to an acceptable margin.

The inversion process by NN is divided into 2 parts as illustrated in Figure 1. At the training stage, the NN is being characterized by the training data provided by the forward model. At the testing stage, the NN is ready to do the inversion when it is fully trained, using the data from the Special Scanning Microwave Imager (SSM/I) on a Defense Meteorological Satellite Program (DMSP) satellite.

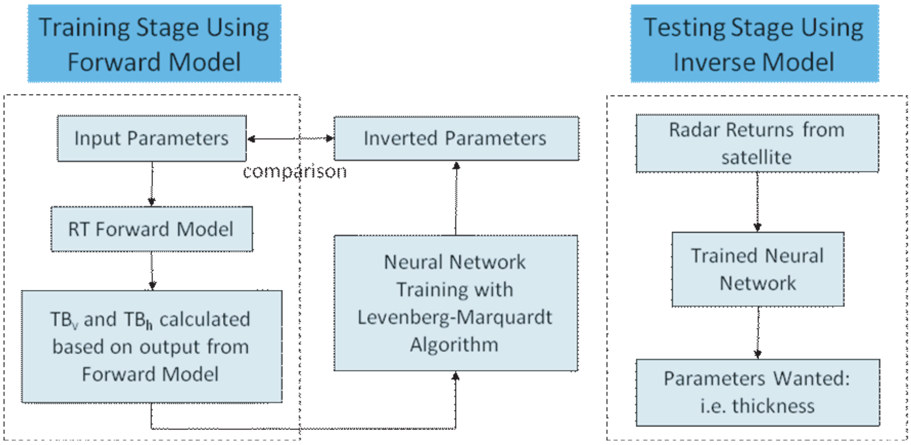

Figure 1: The training stage and the testing stage involving the Neural Network for the sea ice thickness inversion process.

3. SEA ICE THICKNESS RETRIEVAL BY GA

The Genetic Algorithm (GA) is a random search technique that would provide an optimal solution to a problem. The GA encodes the candidate solutions from the existing population into sequence of numbers that are called chromosomes. These chromosomes undergo the process of natural selection where the fitter chromosomes are more likely to survive and pass their traits to the next generation by a reproduction process called crossover. Crossover happens between 2 chromosomes to create new off springs by switching genes at a random point in the chromosomes. Mutations cause small random changes in a chromosome and introduce diversity to the population at a small probability of P_m. The chromosomes are evaluated with an objective function to determine their fitness. The process repeats until a solution has been found. The process flow of the GA is shown in Figure 5. Again, the Special Scanning Microwave Imager (SSM/I) on a Defense Meteorological Satellite Program (DMSP) satellite is utilized for validation of the inversion result.

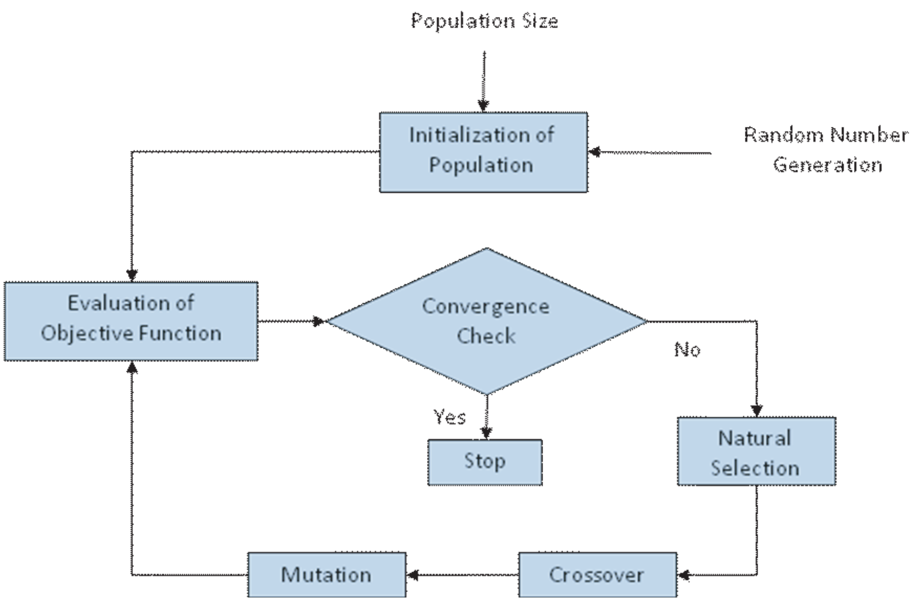

Figure 2: The process flow of the genetic algorithm.

4. RESULT COMPARISON OF NN AND GA

Simulation was first carried out by using the RT-DMPACT model at a frequency of 19 GHz to calculate the various brightness temperatures data set for different sea ice parameters as shown in Table 1, by varying the sea ice thickness.

Table 1: Estimated input parameters for the RT forward model.

Volume fraction	5–10%
Scatterer radius	0.25–0.50 mm
Effective dielectric constant of top layer (air)	$1.0 + j0.00$
Scatterer dielectric constant (brine)	$18.4\text{–}j28.2$
Background dielectric constant (sea ice)	$3.17\text{–}j0.06$
Effective dielectric constant of bottom layer (lower half space)	$18.4\text{–}j30.2$

These data sets are then provided to the NN for training purpose before the inversion process could be made. The inversion result (thickness) is compared to that of the training data sets for validation, shown in Figure 3. For GA, a search routine is setup to look for suitable sea ice thickness with the corresponding brightness temperatures profile. The inversion result from GA is shown in Figure 4.

Figures 3 and 4 show the comparison of the inversion result from NN and GA to that of the theoretical result from the forward scattering model. The general trend is that both approaches yield similar results in terms of sea ice thickness in meters. To further test them in real sea ice cases, we have decided to pick the test sites located to the North West of Beaufort Sea, in the Arctic Ocean around the longitude of 152.641487W–155.436310W and the latitude of 80.591475N–80.648062N.

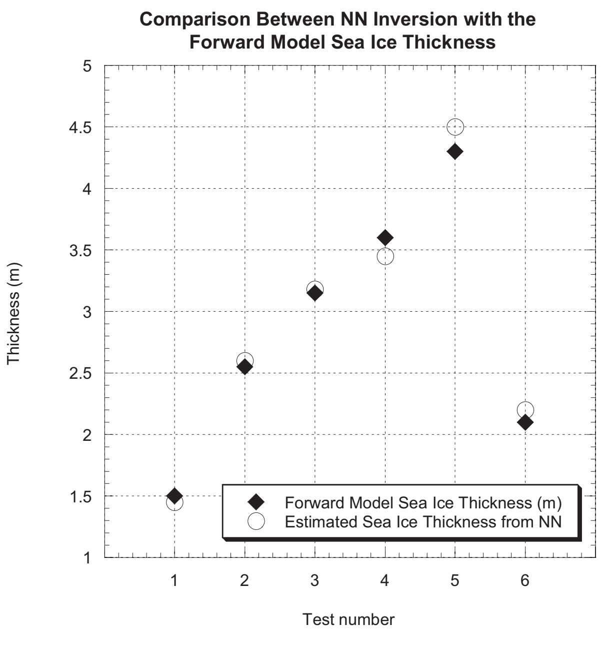

Figure 3: Inversion result from NN compared to that of the forward model.

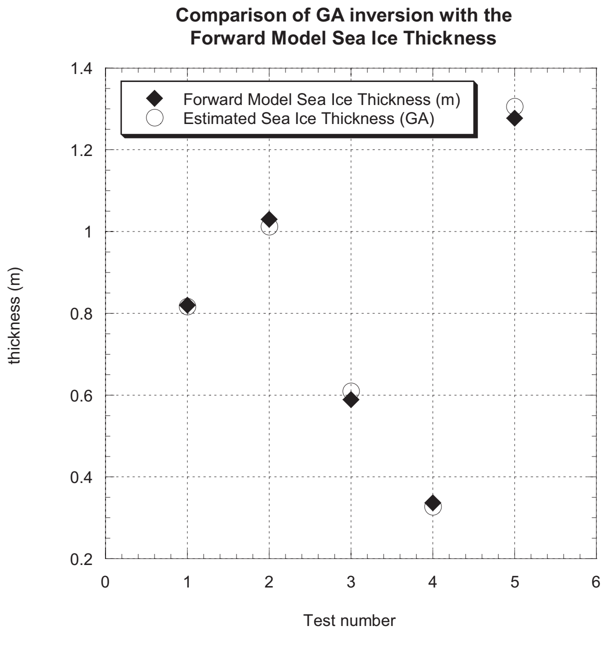

Figure 4: Inversion result from GA compared to that of the forward model.

Figure 5 shows inversion result for both NN and GA by using brightness temperature profile from the Special Scanning Microwave Imager (SSM/I) on a Defense Meteorological Satellite Program (DMSP) satellite dated 19th September 1997. The Arctic sea ice thickness is collected from the submarine upward looking sonar measurement data. The measurement data can be found in the SCICEX-97 data on National Snow and Ice Data Center website http://nsidc.org/data/g01360.html. We can see that the inversion results from NN and GA are quite close to that of the thickness measurement data.

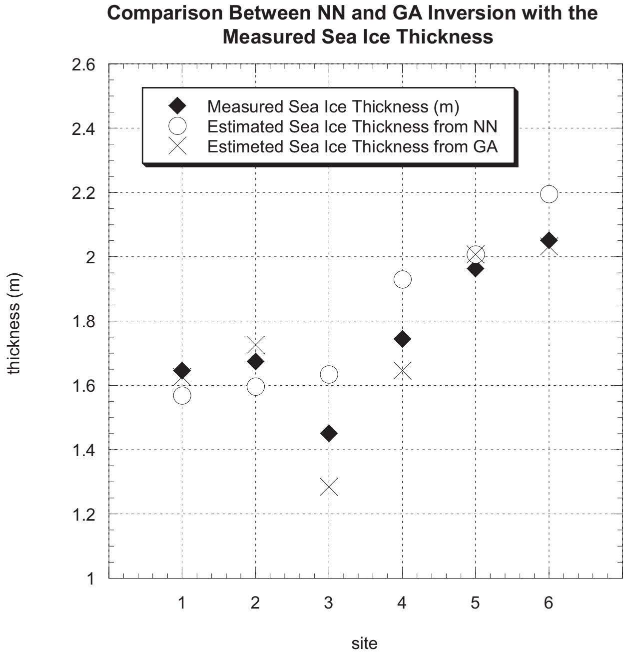

Figure 5: Inversion result from NN and GA compared to the forward model result.

5. CONCLUSIONS

In this paper, two approaches for sea ice thickness retrieval is been presented, one being the NN approach and the other by using GA. These two approaches are used to retrieve sea ice thickness from passive microwave remote sensing. The applicability for both approaches has also been studied. The results from the two approaches show interesting and promising results and indicate that sea ice thickness retrieval using passive microwave remote sensing is possible.

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