AI-BASED FAST COMPUTATION OF NONLINEAR WAVE ENERGY TRANSFER

Auriane Laurent, Coastal Engineering Laboratory, University of Tokyo, auriane.laurent@g.ecc.u-tokyo.ac.jp
Yoshimitsu Tajima, Coastal Engineering Laboratory, University of Tokyo, yoshitaji@coastal.t.u-tokyo.ac.jp

INTRODUCTION

Spectral wave models compute the wave spectra's spatiotemporal growth, propagation and dissipation processes by considering the energy balance equations with several source terms. These source terms account for physical processes such as wind-induced growth, energy loss through white-capping, bottom friction, breaking…, and nonlinear energy transfer through nonlinear wave-wave interactions. Although nonlinear energy transfer was fully and theoretically described sixty years ago (Hasselmann, 1962), its formula's computational cost, due to multiple convolutions on the 2D spectrum, prevents direct implementation in wave models. Following Hasselman (1962), different authors (Hashimoto et al., 1998; Komatsu & Masuda, 1996; Webb, 1978) enhanced the computation algorithm, reducing the required computation time by a factor of 300. Concomitantly, (Hasselmann S & Hasselmann K, 1985) proposed the Discrete Interaction Approximation (DIA) as an alternative computation method 600,000 times faster than the naive implementation of the original Hasselmann formula, making it the preferred way to account for nonlinear energy transfer in most spectral wave models. The gain in computation time is paid for in accuracy, especially when studying wind-induced wave growth. Because Neural Networks (NN) have shown their ability to grasp highly nonlinear behaviors and their capacity to accelerate computations, several authors (Krasnopolsky et al., 2002; Puscasu, 2014; Tolman et al., 2005) proposed Neural Network Interactions Approximations (NNIA) as an accurate substitute of DIA.

Nevertheless, they did not benefit from the recent advances in image based NNs, and their models required major mathematical assumptions and precise model tuning according to the type of spectrum considered.

We aim to propose a convolutional NN architecture to predict nonlinear energy transfer for a wide range of spectra without any hypothesis on the spectrum shape.

METHODS

To ensure that our 100,000-spectrum dataset encompasses a variety of shapes and amplitudes, we randomly generated each wave spectra as a summation of a random number of JONSWAP spectra defined by random wind speeds, fetches, directions and peak enhancement parameters. By doing so, we had single-peaked spectra and more complex spectra with multiple peaks. Fig. 1 shows an example of a two-peaked spectrum representing the combined influence of swell and local wind-induced waves. We then computed 2D nonlinear energy transfer using the method presented by Webb (1978) for direct numerical integration of the Hasselmann formula. The obtained set of nonlinear transfers was used as teaching and validation data sets.

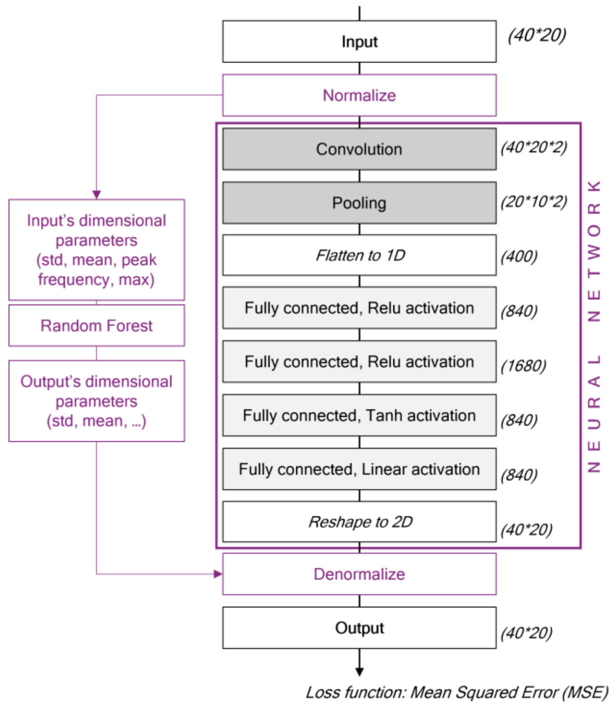

Figure 1: AI-model architecture

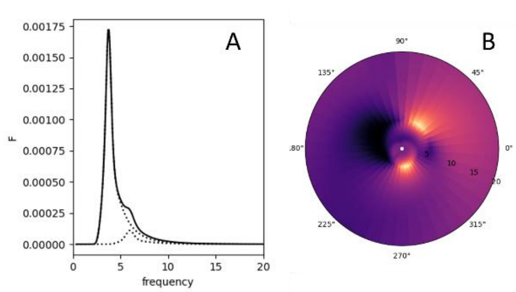

Figure 2: Example of two-peak-spectrum generated: A)1D frequency spectrum, B) 2D frequency-directional spectrum.

The present AI-based NNIA model (architecture shown Fig.2) is composed of two parts: the one, based on NN, predicting the normalized 2D pattern of the nonlinear energy transfer from the normalized 2D spectrum, and the other, based on a random forest, retrieving the amplitude of the nonlinear energy transfer based on the 2D spectrum dimensional parameters (mean, std, and peak value and location). In Fig. 2, numbers indicate the data dimension, our input and output data being a 40 x 20 2D matrix in the direction and frequency components, respectively, as shown in Fig. 3.

Previous studies (Krasnopolsky et al., 2002; Tolman et al., 2005) had decomposed the spectrum and the nonlinear energy transfer onto two orthogonal bases of functions. They then made the NN predict the vector of coordinates of the nonlinear transfer in its base using the spectrum's vector of coordinates. Our approach proposes to use the raw 2D data of the spectrum and nonlinear transfer directly, thus avoiding pre- and post-processing questions. We used convolutional layers to make the NN grasp the input patterns, then flattened the 2D input into a succession of dense layers (5040 neurons distributed over 5 dense layers). We then reshaped our output to 2D.

NN training showed that the normalization of the spectra is essential to yield accurate prediction of small amplitude spectra. A Principal Component Analysis on the spectrum dimensional parameters (e.g., mean, std, max, absolute integral, peak frequency) revealed four parameters (peak frequency, 1D std, 2D mean, 2D max) were needed to retrieve the mean and standard deviation of the output.

RESULTS

The NN offered convincing results in predicting the 2D pattern of normalized nonlinear transfer, even on complex multi-peaked spectra (Fig. 3). The random forest also successfully predicted the standard deviation and the mean better than DIA in 91% and 82% of cases, respectively. It retrieved the standard deviation at a precision of ±50% for 89% of spectra (80% for the mean respectively) (Fig.3). After combining the NN output and the random forest result, the comparison with DIA showed that the present NNIA gives a better approximation than DIA in more than 92% of cases (in terms of NMSE). In addition, the median NMSE for DIA was 0.6 whereas NNIA achieved a median NMSE of 0.01. NNIA was especially efficient in predicting multi-peaked spectra (better than DIA for 97% of them). The computation time was more than 3000 times shorter than the exact Hasselman method and comparable to the one of DIA (4 times longer).

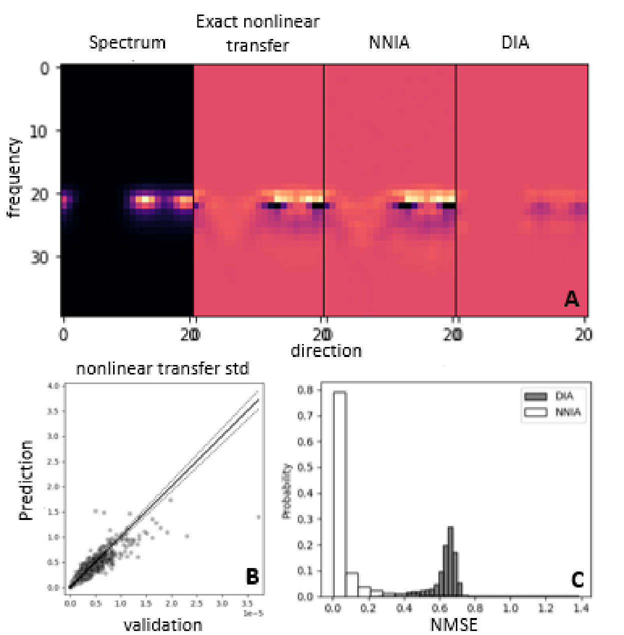

Figure 3: A) Result of NN prediction for a double-peaked spectrum. B) Performance of the Random Forest in predicting the nonlinear transfer std. C) Histogram of the NMSE for DIA and NNIA.

DISCUSSION

This novel approach in the NN-based computation of nonlinear energy transfer seems promising. Further research should discuss expanding the dataset to a broader sample of spectra, including real-life records of stormy or unusual wave conditions. Because we did not optimize the NN or the NN-wave model communication, additional work is required to thoroughly assess the gain in computation time.

Other works (Makarynskyy, 2004; Makarynskyy et al., 2005) have focused on using AI to predict the wave condition. Instead of modelling all physical processes (such as convection, white capping or wave breaking) at once by IA, our approach focuses on modelling the nonlinear interactions, thus improving the overall wave model explicability and limiting error sources. Future work could compare the precision and computation time between wave models using either exact computation, DIA, AI prediction for the nonlinear energy transfer term and fully AI-based wave models on real-life wave studies covering diverse conditions and scales.

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