Can digital techniques be a supplementary or alternative tool for marine hydrodynamics?

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1. Digital technique as an analysis tool

Recently, the application of digital techniques in our lives is evident. Digital technology is already becoming common in most areas of life that can be felt with the skin, such as home appliances or autonomous vehicle operation. Furthermore, the application of digital techniques is spreading to the traditional fields of mechanics, and marine fluid dynamics is not an exception. The terms such as machine learning or digital twin are now popular in recent technical papers.

In the very near future, digital techniques will become firmly established as one of methods for analyzing engineering problems. Until now, we have applied mathematical, experimental, and numerical analyses for various mechanical problems in engineering, but now it seems that there is a new option: digital technique (see Fig.1). For the researchers who prefer traditional techniques, digital techniques have too weak background in physical and theoretical aspects. This is obviously true, and understanding this limitation is very important when applying digital techniques. Nevertheless, this new technique can provide complementary capabilities to the three existing analysis techniques. Furthermore, it may provide solutions to engineering problems that are extremely difficult or require too much time to analyze if the existing techniques are applied.

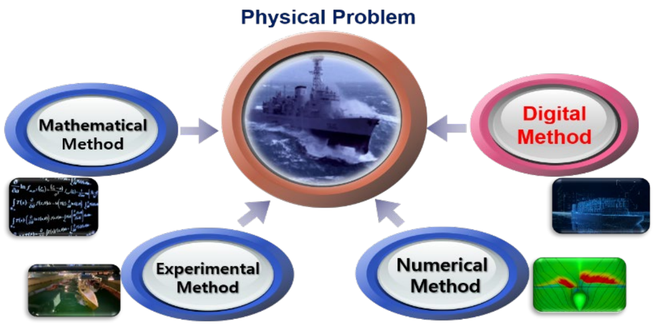


Figure1: Analysis tools for marine hydrodynamic problems

This abstract introduces three cases which demonstrate how digital techniques can be applied in the field of marine hydrodynamics. In these cases, it is shown that digital techniques can be applied both a narrow scope and in the overall scope of the engineering problems.

2. Problem 1: Surrogate model of calm-water resistance for hull-form optimization

Hull-form design is one of major tasks in ship hydrodynamics, and a lot of effort has been made to optimize the hull form. The hull-form optimization carried out in shipyards is mainly to minimize resistance in still water, and the digital technique that can be applied in this optimization process is to predict resistance through a surrogated model rather than calculating it through numerical computation or experiments.

Such an example can be found in the works of Shuguang[1]. They introduced a hull-form optimization including total resistance and speed loss in actual wave conditions. The hull-form optimization process requires a very large number of resistance analyses, which requires an enormous amount of time and effort. Regression equations based on experimental data were used in the past, and recently, CFD has been partially applied. However, Suguang et al. used CFD to secure the metadata of calm-water resistance for various hull-parameter changes in advance and then applied this to the optimization process.

Fig. 2 shows an example of hull-form variations of KVLCC2 and its metadata based on CFD computation. In this case, the change of hull form, particularly the bow part, is controlled by five control points defined on the ship surface. The calm-water resistance C_t and geometric properties, e.g. ship length, buoyancy center, and wetted surface, are dependent on the change of hull form, i.e. movement of five control points. To replace the CFD computation for hull-form optimization, a radial-basis-function(RBF) surrogated model is applied, which has the form of Eq.(1).

$$C_t(X) = \sum_{i=1}^{N} \alpha_i \phi(\| X - X_i \|) + \beta p(X) \tag{1}$$

where α and β are the interpolation coefficients and $\phi(r)$ is the radial basis function. X means the design variables, i.e. the movement of five control points. In addition, the term $p(X)$ indicates any polynomial function. α and β are obtained by applying the design variables of the i-th training case chosen from the resistance metadata. The details can be found in [1].

Fig. 3 shows the leave-one-out cross-validation on training data for C_t when the RBF is $\phi(r) = r^2 \log(r)$, showing better agreement for larger number of training data. It is obvious that the surrogate model provides a good correspondence with CFD computation when the training number is enough.

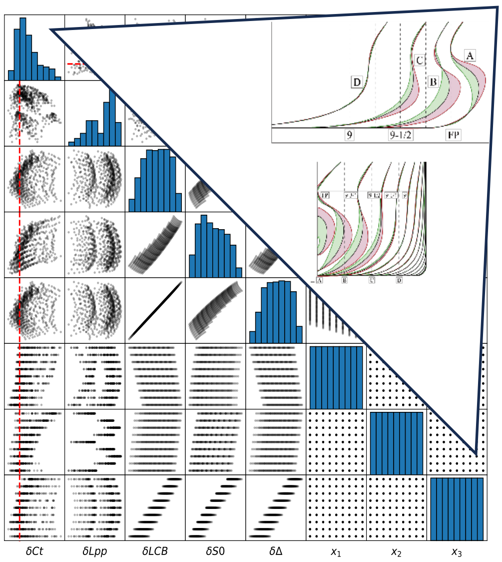


Figure 2: CFD metadata of calm-water resistance: KVLCC2, Fn=0.142 [1]

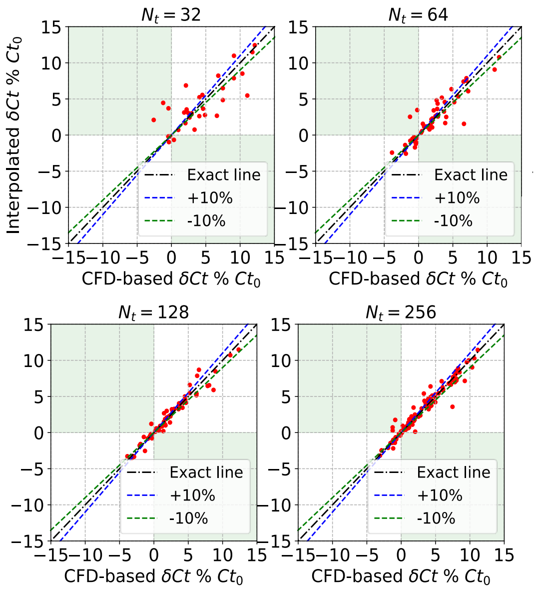
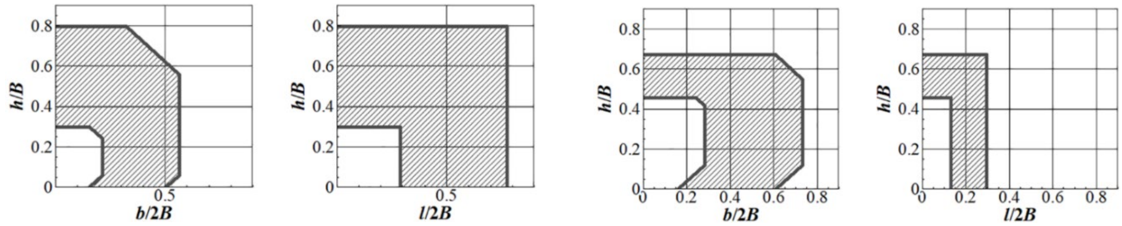


Figure 3: Leave-one-out cross-validation on training data for calm-water resistance [1]

3. Problem 2: Artificial neural network scheme for sloshing load prediction

Sloshing experiment for industrial projects is very time- and cost-consuming. If we can reduce the test cases or predict the loads without experiment, it will be extremely beneficial. Ahn and Kim[2] introduced the application of an artificial neural network(ANN) scheme for the prediction of sloshing impact pressure on the tank of LNG carriers. They utilized the database of Seoul National University, which was extracted from about 100 tank models. At each project, 200~400 test cases with different filling and ocean wave conditions were considered. That is, the database has a lot of existing measurements for different tank shapes and excitation conditions. Ahn et al.[3] first organized many of these data based on data mining techniques, and used this to estimate sloshing ultimate load by applying the ANN technique.

Fig. 4 shows the range of the tank shapes of their database, normalized with respect to the mid-tank breadth of 138,000m^3 LNG carrier. Fig. 5 shows the scatter diagram of pressure coefficient, measured on different regions of the tanks, for various wave conditions. Since the ship motion depends on the wave characteristics, the different wave spectra mean different excitation conditions. Using data mining schemes, we can find some important correlations between input parameters and output results, which provide keys to understand the physics involved in sloshing occurrence. Fig. 6 shows This figure compares the experimental-based and ANN-based prediction results for the extreme load during 3 hours. The tank models are two actual LNG tanks of different LNG carriers. What is important to note in these results is whether the ANN-based prediction of the extreme load in the same sea state expected from the tanks mounted on two ships, the conventional model and the optimum model, matches the experimental results. Fig. 6 clearly shows the validity of the ANN predictions.



(a) Tanks of LNG carrier (b) LNG fuel tank

Figure 4: Range of tank models in SNU's database [2]

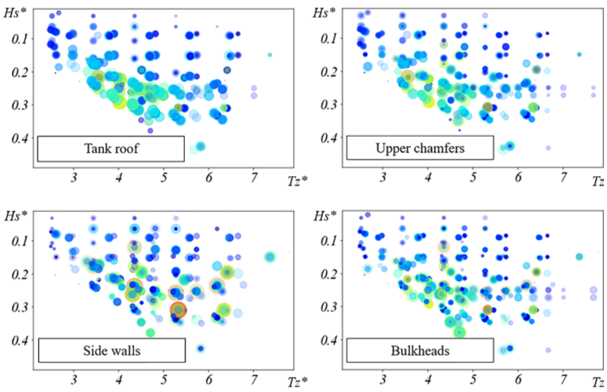


Figure 5: Scatter diagram of pressure coefficient with respect to significant height and mean period of ocean wave spectrum [3]

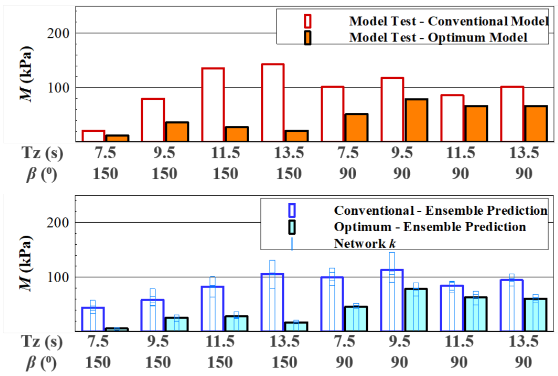


Figure 6: Comparison of extreme pressure between experiment(up) and ANN(down) prediction: two different tanks under low filling condition [2]

4. Problem 3: Machine learning for ship motion in waves

Recently, ship motion analysis results using machine learning(ML) techniques have been introduced in many papers. However, what is important in this analysis is that the physical mechanism involved in the ship motion must be understood, and such physical mechanisms must be reflected in digital techniques. For example, the memory effect is important for the motion of a ship in waves, and how much time to apply to the training data in ML can be determined by considering theoretical values related to the memory effect such as the retardation function rather than simply determining it through a parametric study.

Actual ship motion is dependent critically on ocean waves, but almost all published ML-based ship motion analysis treats ocean waves as a simple input signal. In this abstract, we introduce a more advanced method of ML analysis applied to spatiotemporal data as an example. Lee et al.[4] improved the accuracy of prediction by applying input containing both spatial and temporal data of ocean waves to ML.

Fig. 7 shows the concept of the application of spatiotemporal data for ML application. The NxN sets of spatial data are compressed into smaller data set and applied eventually as a single vector after repeating the compression. The training of ship motion is based on a well-known LSTM scheme. Fig. 8 shows an example of heave RAOs for different wave headings. In this figure, HD means the solution of strip theory and INN indicates the results of the machine learning scheme using spatiotemporal data. It should be mentioned that the motion signals are obtained using an impulse-response-function method and weakly-nonlinear method. Fig. 9 shows an example of ship motion in oblique irregular seas, showing almost identical results with a hydrodynamic motion solver.

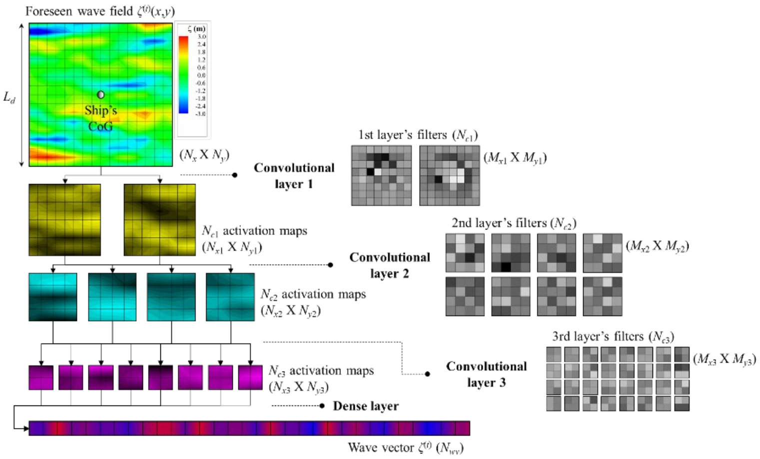


Figure 7: Convolutional neural network system for wave-field data [4]

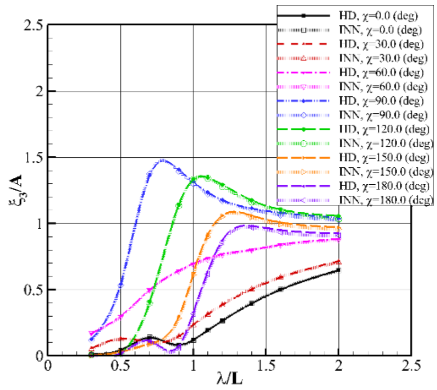


Figure 8: Heave RAOs for different wave directions: KVLCC2 [4]

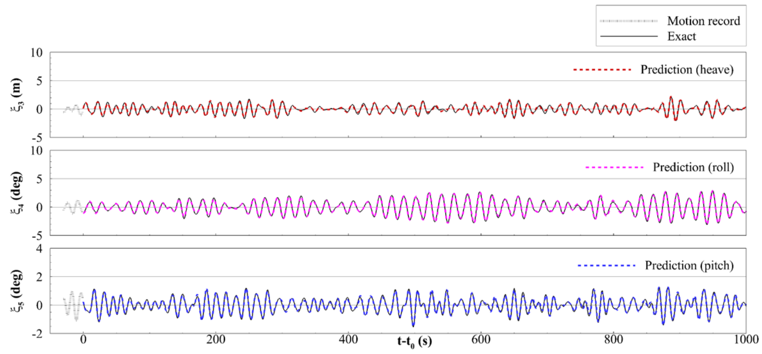


Figure 9: Ship motion in irregular sea: Beaufort scale 8, 60° heading, heave-roll-pitch motion (from top), 9x9 spatial data for waves [4]

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