CEMRACS 2023 mini-project proposal

2 pages maximum (references included)

Title: Multidimensional integration using machine learning and Monte Carlo methods for acoustic predictions

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1. Context

It has been shown that in deep water ocean, the background noise can be dominated by anthropogenic sources. Over the last decades, the noise pressure spectrum increased of at least 12 dB compared to pre-industrial level [1]. Underwater noise radiated from large vessel, which is predominant in the frequency range [5 – 300 Hz] is becoming a growing concern since it has been shown to coincide with audible range used by marine wildlife [2]. Thus, it can have a significant impact especially on species that have evolved to exploit hearing as their primary sense. In order to design vessels meeting regulatory guidelines [3] that define a maximum radiated pressure level, it is necessary to understand the various noise generation mechanisms involved and to develop prediction methods associated to each of this mechanism. Two contributions to the total radiated acoustic field radiated by a ship can be distinguished: the vibratory contribution, produced by the excitation of the hull by turbulent eddies and machinery noise, and the purely hydrodynamic contribution near the propeller produced by both the cavitation and the turbulence and by their interaction with propeller blades. Many of the existing prediction methods, based on complete numerical simulation of the turbulent flow, are too expensive for industrial underwater applications.

Recently, an approach based on the Lighthill acoustic analogy and the use of a tailored Green function [4] has been proposed. It allows to consider realistic geometries and can be used from a numerical simulation of the mean flow. However, it requires the computation of a 6-dimensional integration, which is computationally expensive. A well suitable type of method for solving integrals with a large number of dimensions are those based on stochastic techniques: Monte Carlo methods. While the error made by deterministic quadrature methods increases exponentially with the number of dimensions, the one associated with probabilistic method simply does not depend on it. It can be shown [5] that the error decreases in the worst case (i.e., without using any adaptative method) as N^1/2, where N is the number of samples of the integrand function. The counterpart of Monte Carlo integration methods is that a high integration precision cannot be achieved. But a high precision is not necessary since a targeted +-1 dB precision on the radiated sound pressure level is reached for a relative error on the integration up to 25%. There are several adaptative methods used to reduce the integration error [6] and the most popular ones are importance sampling and stratified sampling. On the one hand, the idea of importance sampling is to modify the probability density function, which is uniform in the classical Monte Carlo integration method, in order to concentrate the integrand evaluations points in the regions of largest magnitude. On the other hand, the stratified sampling technique consists in the subdivision of the integration domain into sub-domains over which the integral will be evaluated. Currently, the computation of the 6-dimensional integral is made with the VEGAS algorithm, introduced by Lepage in 1978 [6]. VEGAS is known to be very efficient if the integrand can be approximated by a separable function. However, for acoustic prediction models, all the variables are strongly correlated, and it is expected that other techniques could yield better performances.

2. Description and objectives

In order to be able to predict the underwater noise radiated by a full-scale ship, it is necessary to reduce as much as possible the time required to compute the 6-dimensional integral. Recently, various approaches based on hybrid Monte Carlo algorithm, generative machine learning models have been proposed [7] [8] [9] or neural network integration [10]. The objective of this project is to determine the best alternative to the VEGAS algorithm in the context of acoustic predictions i.e., for integrands with large peaks, strongly correlated variables and oscillatory behavior at high frequency.

3. Proposed methodology

The first step will be to conduct numerical experiments to compare the classical Monte Carlo quadrature methods with new machine learning based methods. The second step will be to define an integrand representative of what is encountered in the context of acoustic predictions. The last step will consist in drawing conclusion of this comparison and to quantify the performance gain that can be expected from the use of machine learning techniques.

4. Software requirements

The selected solution will be preferably implemented in C++ or Python.

References

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