Drag reduction of KCS based on extended FFD method and EGO algorithm

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Abstract

The research presented in this paper is aimed at improve drag performance of a ship based on a flexible hull form modification method and an effective optimization algorithm. To obtain a series of practical new hull forms, a good ship modification method is needed first. Free-form deformation (FFD) method is a good deformation method to be widely applied in many shape design fields, such as aircrafts, Remote Operated Vehicles (ROV), cars and ships. Here, FFD method is extended by adding bending transformation in our in-house ship optimization solver, OPTShip-SJTU. In addition, a better optimization algorithm can greatly reduce computational cost and optimization responsive time. The efficient global optimization (EGO) algorithm has such good properties. It is a Kriging-based global optimization method, making the most of the knowledge of the error of Kriging model to search a cost landscape. In this paper, The KRISO Container Ship (KCS) is used as the initial ship, locally modified in the front half of the ship by FFD method mentioned above. The objective function (the wave-making resistance) is evaluated by the potential theory, Neumann-Michell method. Through the EGO algorithm, the drag of the initial ship is fast and efficiently optimized and the corresponding optimal ship is obtained. To verify the optimal result, the optimal ship is compared in detail with the initial one in the aspects of body lines, pressure distribution of ship surface, wave elevation, etc. It turns out the methods here are well applied to the ship optimization problem.

Keywords: drag performance; ship optimization design; extended FFD; EGO

Introduction

CFD is currently playing an increasingly important role in numerical prediction of ship hydrodynamic performance. The problem of long model test period and high cost is solved to a large extent. The ship hull optimization also began to leave the traditional design mode. A simulation-based design (SBD) mode emerged, that is, Numerical prediction based on CFD was used to evaluate the hydrodynamic performance, and the optimization algorithm was used to minimize the ship's hydrodynamic performance and improved ship hull lines. At present, a large number of scholars are studying such problems and have partly and successfully applied them to engineering practice.

However, ship optimization design requires a large amount of numerical calculation, which greatly increases the time and cost of CFD calculation. It needs to be achieved by means of approximation and parallel techniques. There is no clear direct expression between the hydrodynamic performance of a ship and the deformation parameters of a ship. The approximation technique implicitly expresses the relationship between the design variables and the objective function by mathematical means to construct an approximate model (Wu J. W., 2017; Liu X. Y. 2017), so that there is no need to call the CFD prediction of the hydrodynamic performance in the optimization process. The calculation is directly invoked by the approximation model, which greatly reduces the optimization design time and calculation cost. Then for only optimization according to the approximate model, there are the following problems: Firstly, the accuracy of the approximate model needs to be accurate enough before optimization, and enough sample points are needed, otherwise the result is unreliable and the optimization fails; at the same time, the obtained optimized solution needs to be calculated again by high-fidelity CFD method or model test to confirm.

This paper adopts an efficient global optimization algorithm, also called the sequential global optimization algorithm based on approximation model. This method makes full use of the approximate model, and combines the estimation results of the existing approximate model with the uncertainty of the approximate model and the optimization algorithm. The high-precision calculation of additional sample points is needed by the above method. It continuously improves the accuracy of the approximate model and continuously explores the optimal value. An EI criterion (Expected Improvement) was proposed by Donald R. Jones in 1998. The sample points are needed by optimizing this criterion, which was successfully applied to the optimization of mathematical functions, especially high-dimensional functions. The convergence speed is much larger than many algorithms such as genetic algorithms. Later, more developments were made (Weihs. C, 2016) from the original single-objective optimization to multi-objective optimization (Seulgi, Y. I. 2014), and It began to be applied to engineering practice, including the design of airfoils, the volume of the oil pump and other optimization design problems (Jeong S, et al, 2015; Yi S, 2015)

In addition to the need for better optimization algorithms, the transformation method for ship lines must be further studied. Free-form deformation is a good and mature method to modify ship lines and it is extended based on the FFD transformation method that has been developed. The object can be achieved bending deformation in the presence of continuity. The method is applied to hull form transformations effectively and efficiently especially for local shapes deformation such as bulbous bow and two-skeg stern.

In the first half of this paper, the FFD method and EGO method will be briefly introduced. In the second of this paper, the methods will be applied to the optimization problems of ship design of KCS.

FFD method

Free-form deformation (FFD) method is a good choice to modify hull form locally. FFD method was first described by Thomas W. Sederberg and Scott R. Parry (1986) and was based on an earlier technique by Alan Barr (1984). Its basic idea of this method is embedding a ship or the region of the ship to be deformed within a parallelepipedical 3D lattice regularly subdivided. Then it can modify the surface shape of a ship by the following relationship.

$$X_{ffd} = \sum_{i=0}^{l}\sum_{j=0}^{m}\sum_{k=0}^{n} B_{i,j}(s) B_{j,k}(t) B_{i,k}(u) Q'_{i,j,k} \tag{1}$$

Wherein $Q'_{i,j,k}$ is the coordinates of the control points on the lattice, while X_{ffd} is the coordinates of the points of the ship surface. B is Bernstein polynomial, l, m, n are the numbers of the control points along the x-axis, y-axis, z-axis direction, respectively. Through changing the movable number, direction and displacement of the control points, the different ship surfaces can be easily obtained. Figure 1 is a sketch of a ship's bulbous bow deformation through the FFD method. Given the control points' rotating angle, the entire lattice is deformed, so that the bulbous bow is bent.

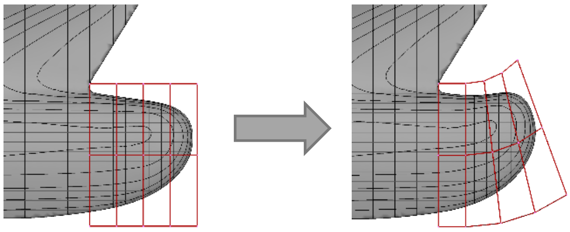


Figure 1 The application of the FFD method

In the paper, two lattices (Fig. 2) are used to modify the shape of the ship's front half part, the small lattice to modify the shape of the bulbous bow including the length, width, and degree of curvature, and the large one to modify the fatness of the ship’s front half. A total of 7 design variables related to the shape deformation are involved in the optimization problem. Then, 35 sample hulls are generated through design of experiments.

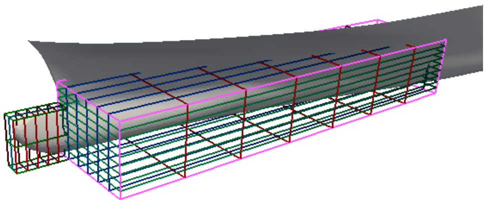


Figure 2 Two lattices used by the FFD method

Kriging Model

Kriging model (Simpson et al., 1994, 2004) is developed from mining and geostatistical applications involving spatially and temporally correlated data. This model combines a global model and a local component:

$$y(x) = f(x) + z(x) \tag{2}$$

where $y(x)$ is the unknown function of interest, $f(x)$ is a known approximation function of x, and $z(x)$ is the realization of a stochastic process with mean zero, variance σ^2, and non-zero covariance. With $f(x)$ and $z(x)$, the kriging model can build the surrogate model between the input variables and output variables.

The kriging predictor is given by:

$$\hat{y} = \hat{\beta} + \mathbf{r}^{\mathrm{T}}(x)\mathbf{R}^{-1}\left(\mathbf{y} - \mathbf{f}\hat{\beta}\right) \tag{3}$$

where y is an ns-dimensional vector that contains the sample values of the response; $\mathbf{f}$ is a column vector of length n_s that is filled with ones when f is taken as a constant; $\mathbf{r}^{\mathrm{T}}(x)$ is the correlation vector of length n_s between an untried x and the sampled data points $\left\{x^{(1)}, x^{(2)}, \ldots, x^{(n_s)}\right\}$ and is expressed as:

$$\mathbf{r}^{\mathrm{T}}(x) = \left[R\left(x, x^{(1)}\right), R\left(x, x^{(2)}\right), \ldots, R\left(x, x^{(n_s)}\right),\right]^{\mathrm{T}} \tag{4}$$

Additionally, the Gaussian correlation function is employed in this work:

$$R(x^i, x^j) = \mathbf{exp}\left[-\sum_{k=1}^{n_{dv}} \theta_k \left|x_k^i - x_k^j\right|^2\right] \tag{5}$$

In equation (3), $\hat{\beta}$ is estimated using equation (5):

$$\hat{\beta} = \left(\boldsymbol{f}^{\mathrm{T}}\mathbf{R}^{-1}\boldsymbol{f}\right)^{-1}\boldsymbol{f}^{\mathrm{T}}\mathbf{R}^{-1}\boldsymbol{y} \tag{6}$$

The estimate of the variance $\hat{\sigma}^2$, between the underlying global model $\hat{\beta}$ and y is estimated using equation (7):

$$\hat{\sigma}^2 = \left[\left(y - f\hat{\beta}\right)^T R^{-1}\left(y - f\hat{\beta}\right)\right] \Big/ n_s \tag{7}$$

where $f(x)$ is assumed to be the constant $\hat{\beta}$. The maximum likelihood estimates for the θ_k in equation (5) used to fit a kriging model are obtained by solving equation (8):

$$\max_{\theta_k>0} \Phi(\theta_k) = -\left[n_s \ln(\hat{\sigma}^2) + \ln|\mathrm{R}|\right]/2 \tag{8}$$

where both $\hat{\sigma}^2$ and $|\mathrm{R}|$ are functions of θ_k. While any value for the θ_k create an interpolative kriging model, the "best" kriging model is found by solving the k-dimensional unconstrained, nonlinear, optimization problem given by equation (8).
the accuracy of the prediction value largely depends on the distance from sample points. Intuitively speaking, the closer point x to the sample point, the more accurate is the prediction $\hat{y}$. This intuition is expressed as

$$s^2(x) = \hat{\sigma}^2\left[1 - r^{'}R^{-1}r + \frac{(1-1R^{-1}r)^2}{1^{'}R^{-1}1}\right] \tag{9}$$

where $s^2(x)$ is the mean squared error of the predictor and it indicates the uncertainty at the estimation point. The root mean squared error (RSME) is expressed as $s=\sqrt{s^2(x)}$.

A kriging-based global efficient optimization algorithm

Traditionally, once the surrogate model is constructed, the optimum point can be explored using an arbitrary optimizer on the model. However, it is possible to miss the global optimum because the approximation model includes uncertainty at the predicted point.
In Fig. 3, the solid line is the real shape of objective function. Eight points are selected to construct the kriging model, which is shown as red points. The minimum point on the kriging model is located near x=16, whereas, the real global minimum of the objective function is situated near x=17. Searching for the global minimum using the present kriging model will not result in the real global minimum near x=17. For a robust search of the global optimum, both the predicted value by the kriging model and its uncertainty should be considered at the same time.

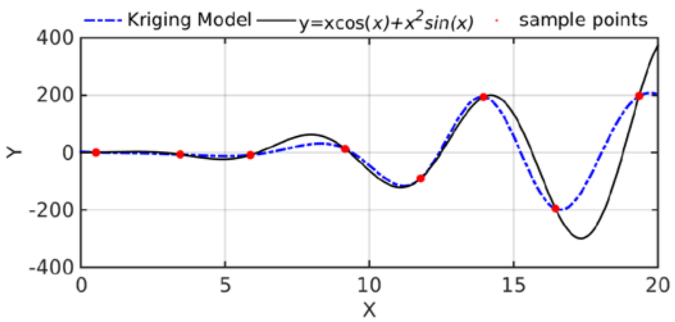


Figure 3. The Kriging model and the real function curve

When Kriging model is built, the mean predicted value and the standard error of the kriging model at any point can be evaluated. Considering the uncertainty of the model, this concept is expressed in the criterion of EI. The EI of minimization problem can be calculated as

$$E[I(x)] = (f_{\min} - \hat{y})\Phi[(f_{\min} - \hat{y})/s] + s\phi[(f_{\min} - \hat{y})/s] \tag{10}$$

Where $f_{\min}$ is the minimum value among n sampled values. Φ and ϕ are the standard distribution and normal density, respectively.

In fact, if we compute the derivative of EI as given in equation (9) with respect to $\hat{y}$ and s, we gets several terms that cancel, resulting in the simple following expressions:

$$\partial EI / \partial \hat{y} < 0, \partial EI / \partial s < 0 \tag{11}$$

It turns out that EI is monotonic in $\hat{y}$ and in s. Thus, we see that the EI is larger the lower is $\hat{y}$ and the higher is s. By selecting the maximum EI point as additional sample point through DE algorithm mentioned above, robust exploration of the global optimum and improvement of the model can be achieved simultaneously.

The overview over the whole efficient global optimization (EGO) procedure mentioned before is shown in Figure 4. First, the initial sample points should be chosen by experiment of design uniformly covering the whole design space. Secondly, an ordinary Kriging model is built and used to predict the objective for each design variable. Thirdly, the expected improvement (EI) balancing between regions of the low mean prediction and of high standard error is constructed to select the next point. The choice of the next sample point is the maximization of the EI value. Next, the objective function in the new point is calculated accurately and used to build a new surrogate model with the initial sample points, thus the next iteration is initiated. Finally, when the EI value is very small after n iterations, i.e., $\max(EI) < \Delta s \cdot (\max(y) - \min(y))$, where Δs is the relative stopping tolerance, or reach the maximization of iteration steps, the loop should be stopped.

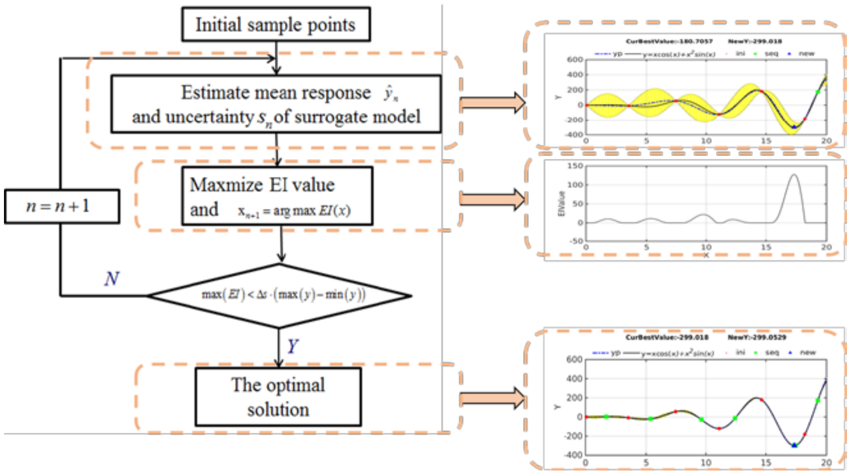


Figure 4. The flow chart of efficient global optimization: on the left, the steps are briefly described; on the right, an example is given (predetermined design points as red dots, the added new points as green squares and the next new point as a blue triangle).

Application of ship optimization design of KCS

In this study, the EGO method was applied to ship hull form design and the optimization of the resistance performance in calm water.

$$f_{obj} = R_w, Fr = 0.26 \tag{12}$$

The design problem is to minimize the wave-making resistance of KCS at the design speed. The extended FFD method mentioned above was applied to modify ship hull form (Fig.5). The design variables are parameters closely related to ship hull form modification. The total 7 design variables in Table 1 are used to define the geometry of ship hull form. The upper and lower bounds of each parameter are determined to avoid unrealistic ship hull geometry.

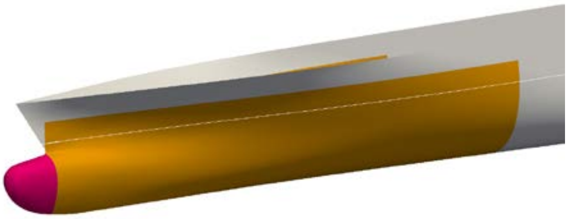


Figure 5. The variable region and the control points distributed on KCS hull by extended FFD method

Table 1. The design variables and their ranges

Design variables	Deformation direction	The bounds
1#	x	[-0.008, 0.01]
2#	y	[-0.01, 0.01]
3#	θ	[-40, 20]
4#	y	[-0.02, 0.015]
5#	y	[-0.015, 0.015]
6#	y	[-0.015, 0.015]
7#	y	[-0.01, 0.01]

At the early stage of optimization design, 49 sample points are spread over the design space and selected by Optimal Latin Hypercube Sampling (OLHS) to obtain a kriging model (Park J. S., 1994). The number of sample points is very important to keep the kriging model accurate in the traditional optimization process. However, in the present kriging model, additional sample points will be added later in the region where the accuracy is not good enough, or the objective function value is lower based on EI evaluation. The wave-making resistance of 49 sample hull form and additional sample points are all evaluated using a potential flow theory, Nuemann-Michell method (Noblesse F., 2013; Wu, J. W., 2016).

The summary of the parameters of EGO method is shown in Table 2. After efficient global optimization search, the total number of sample points reached 79, after adding 30 more sample points (in Fig.6). The objective function converges to the minimum value, 10.5629N, a larger reduction of about 25.13% than the initial value. We just use a PC to finish all the evaluations for about 1.89 hours.

In order to verify the accuracy and efficiency of EGO, we use the traditional optimization method, which firstly enough points are used to construct a surrogate model with sufficient precision (90 sample points are used here), and then the genetic algorithm (GA) is applied to search the optimal value of the surrogate model (in Tab. 3). The optimal ship is obtained through more than 200 iterations, and the wave resistance value reaches 11.1037 N, which is reduced by 21.30%. And the design variables of the optimal hull forms based on two methods are shown in Fig. 7.

The comparison of Table 2 and Table 3 and Figure 6 clearly show the efficiency of the EGO method. It greatly reduces the cost of high-precision numerical calculations. It can be seen from Fig. 7 that the optimized ships obtained by the two methods are different.

Table 2. The parameters of the EGO method

The initial number of sample points	49	The additional number of sample points	30
The number of iterations	30	Optimization time (h)	1.89

Table 3. The parameters of the GA method

The initial number of sample points	90	The number of populations	50
The number of iterations	400	Optimization time (h)	3.12

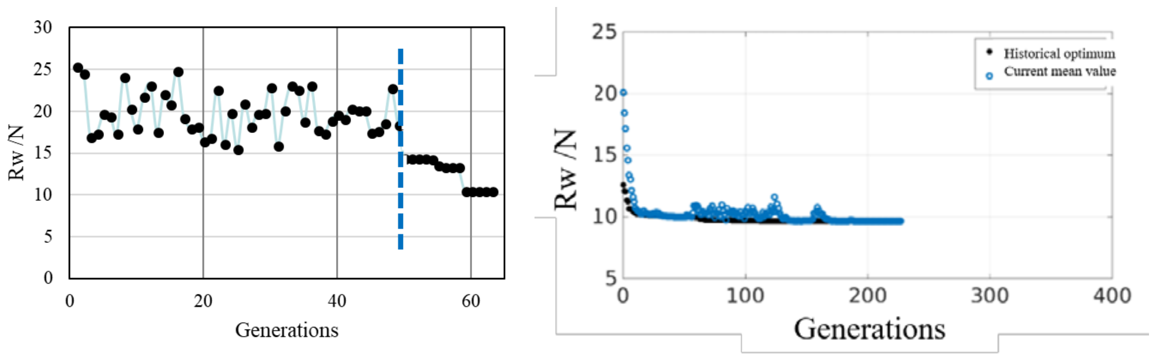


Figure 6. The total numbers of numerical evaluation using the EGO method (left) and the GA method (right) until convergence

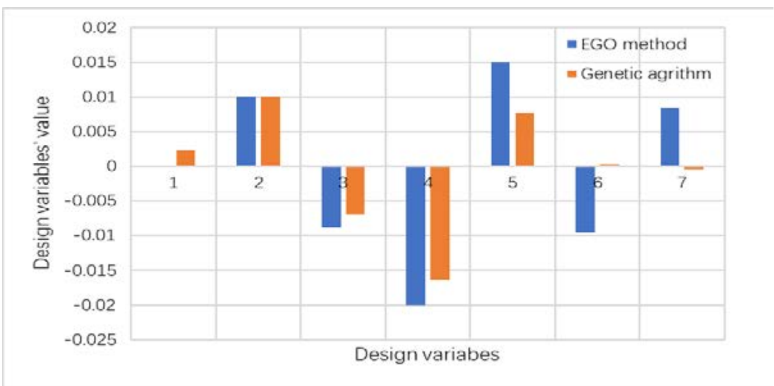
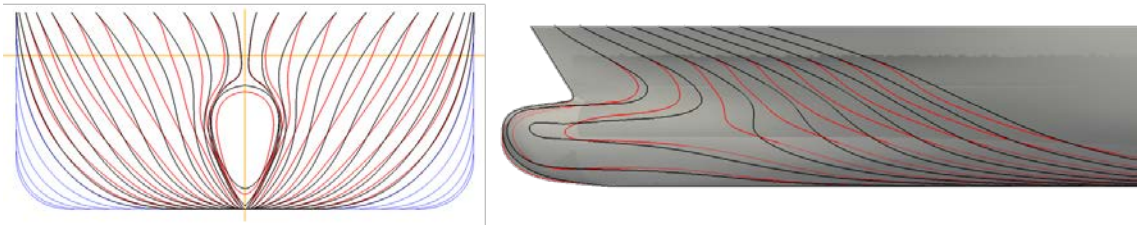
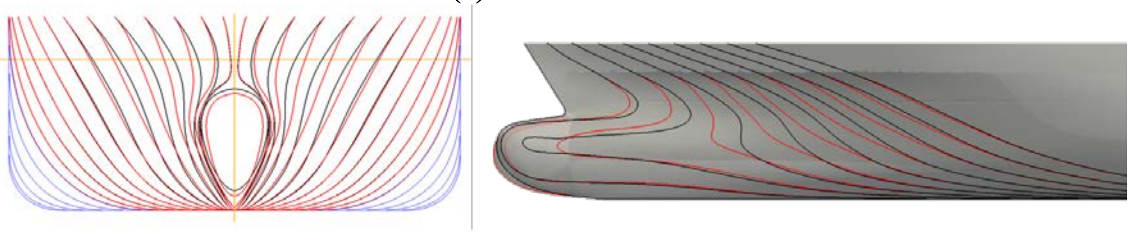


Figure 7. The values of design variables and the optimal solution of the objective function after optimization procedure

The following figures depict the comparisons of body lines and shapes of the initial KCS and the optimal ship based on the two methods. The same changes are as following: first changes have taken place in the waterline of the optimized ships, the waterline near the inlet has become fatter. In addition, the bilge of the optimal ship has become thinner, the bulbous bow has also become thinner and longer, and has slightly been flattened compared to the original ship. The different changes of the optimized hulls based on the two methods happens at the front shoulder of ships. The optimized ship based on EGO method has a large difference from the initial one, while the optimized ship based on GA has basically not changed.

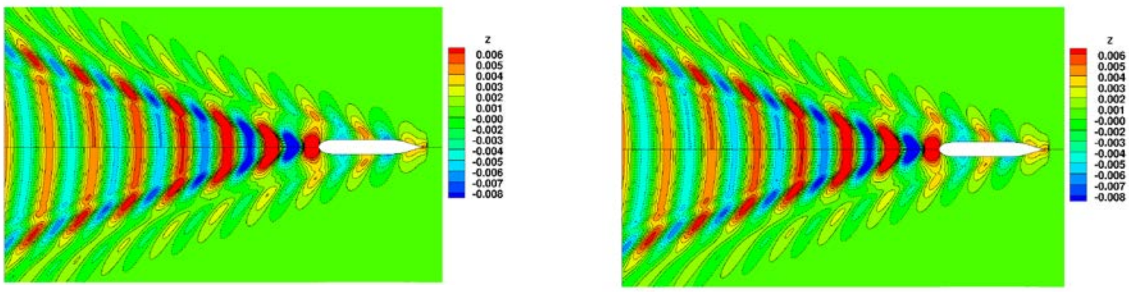


(a) EGO method



(b) GA method

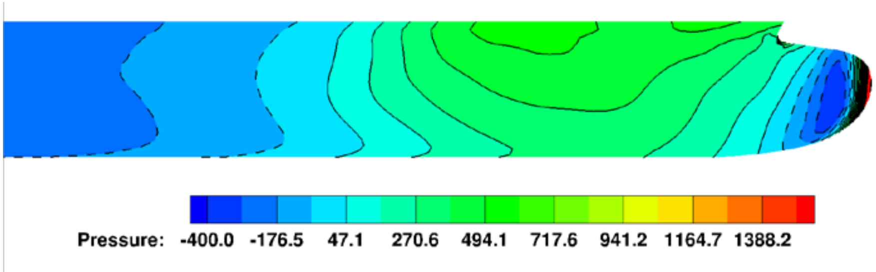
Figure 8. Comparisons of the body lines and shapes between the initial hull and the optimal one



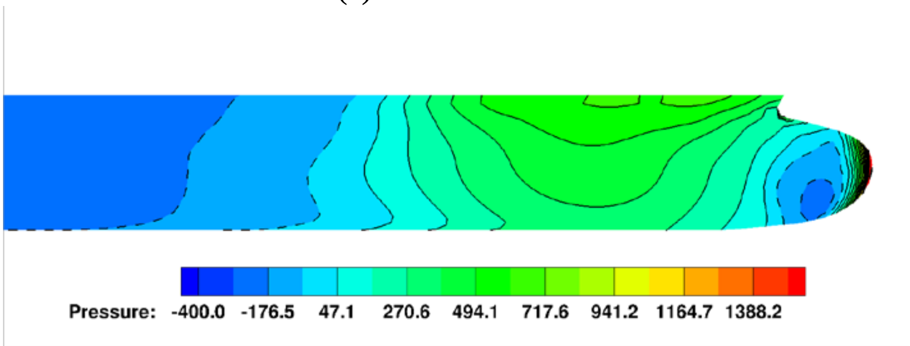
(a) EGO method (b) GA method

Figure 9. Comparison of free surface elevation between the initial hull and the optimal one

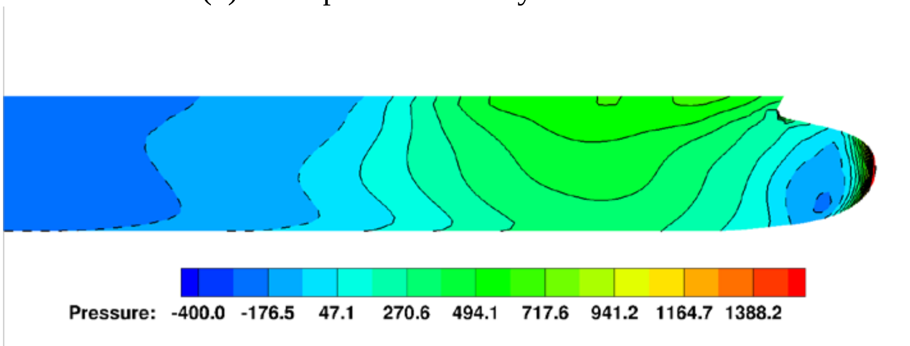
Figure 9 is the wave profile of free surface of the two optimized ships. In contrast, both optimized hulls obtained by two methods generate lower wave than the initial one obviously, thus leads to the reduction of the wave-making resistance of the optimal hull. Also comparing the pressure distribution of the two ships in Fig. 10, the fore parts of the optimal hulls is with lower pressure than the initial one. Here we can conclude that the small variation of the front shoulder of the optimized ships has less effect on the improvement for the wave resistance of this ship.



(a) The initial hull



(b) The optimized hull by EGO method



(c) The optimized hull by GA method

Figure 10. Comparison of pressure distribution between the initial hull and the optimal one

Conclusion and future work

This paper presents a Kriging-based global optimization method, efficient global optimization (EGO), different from the ordinary optimization method. It combines the surrogate modeling with the optimization algorithm. By this method, not only the accuracy of surrogate model is continuously improved but also the solution of the optimization problem keeps searched in the iterative procedure. An FFD method for ship modification is also used to allow the geometry or a part of the geometry to be bent. The two methods are successfully applied to ship hull form optimization design. Based on the comparison of EGO method and the traditional optimization method, the results demonstrate the usability and efficiency of the EGO methods in ship hull form optimization design. In the future, it will be used to the more ship optimization problem, such as the ship hull form design to improve comprehensive hydrodynamic performance, based on entire CFD.

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