Design and optimization of a bio-inspired hull shape for AUV by surrogate model technology

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ABSTRACT
This paper proposes a bio-inspired hull shape (BHS) for AUV by studying and modeling the body shape of humpback whales. Among factors affecting hydrodynamic characteristics, this paper considers both the hull drag and displacement volume to optimize the BHS, which profitably improve the space utilization and voyage of the AUV. The optimization is conducted by a surrogate model using response surface methodology (RSM), during which the translational propagation Latin hypercube design (TPLHD) is adopted to obtain sampling points. In order to verify the optimization results of BHS, the drag computations for BHS and eight typical hull shapes of existing typical or bionic AUVs are performed for comparison under conditions of similar volume, wet surface area, body length and attachments. A scaled-down model of BHS with attachments is then designed, manufactured and carried out a towing tank test. The drag measured in the towing tank test is basically the same as the simulation result, with the average relative error of 3.68% at 4m/s. The result of the shape optimization performed with the RSM is effective. Furthermore, the proposed BHS is highly suitable for underwater vehicles with requirements for longer distance, higher speed or better sensor carrying capacity.

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1. Introduction
In recent years, the role of unmanned underwater vehicles in ocean observation and marine resource exploration has become increasingly prominent (Ishikawa et al., 2004; Newman et al., 2007; Yamamoto, 2015; Zhang et al., 2017). Among them, the autonomous underwater vehicles (AUVs) is an indispensable and important tool for scientific observation and exploration in the marine environment, such as seabed minerals exploration, seabed topography survey, marine living resources survey and search and rescue (Ishikawa et al., 2004). In order to realize wide-area observation of the above tasks, the long-range of an AUV is particularly important, which can be achieved by increasing the energy capacity, improving energy efficiency or reducing power consumption. To prolong the endurance and increase the payload of an AUV, low drag performance and large internal space are required. Thus a carefully hydrodynamic shape design and optimization are indispensable to reduce the power consumption (Zhang et al., 2017).

Thanks to their advantages of high flexibility of operation and long range, there are some typical AUVs developed to survey ocean environment and detect marine resource, such as Autosub 6000 (McPhail, 2009), Echo Voyager (Boeing, 2020), Tethys (Ghalandari et al., 2019), and CR-01 (Li & Feng, 2001). Their sailing speed varies mainly in a range of 0–10 knots. The shape of AUV is mostly revolving or symmetrical, and generally composed of the bow, middle section and tail. The cross-section of the middle section is generally round, but few are ellipse or square. It is a challenge to break through the limitation of the shape of the existing underwater vehicle and develop a new low resistance shape design.

In nature, low drag and excellent streamlined body enable some marine animals to achieve high-speed movement, such as dolphins, sharks, and penguins (Nesteruk et al., 2014). To design a new shape for AUVs to achieve better performance, especially for those with large volume and low drag, the bionic shape design for the underwater vehicle, inspired by imitating the appearance of animals, has become popular and hot research topic (Dong et al., 2020b). The bionic shape has natural advantages in terms of drag, sailing performance, stealth performance, etc. The reduction of turbulence on the shape of a model Humboldt penguin (Parfitt & Vincent,
2005) can cause a significant reduction in boundary layer height, which can reduce the drag by an average of 31%. Moreover, more slender body shapes have been developed by imitating the shape of black marlin, swordfish, indo-pacific sailfish, or mediterranean spearfish. A gliding robotic fish (Dong et al., 2020a; Dong et al., 2020b) is designed and manufactured with a streamline shape of whale shark. That fish can achieve both high maneuverability and excellent gliding performance by equipping with controllable fins and tails. Honaryar and Ghiasi (2018) designed an AUV by imitating the shape of a catfish namely ZRAUV, which has a triangular cross-section hull and is more stable by about 99% compared to regular axisymmetric bodies. By studying the shape of a dolphin according to the principle of bionics, Zheng Xing et al. (Wu et al., 2016) finds that the shape has a distinguished performance of high mobility, low-drag and long-range. The streamlined shape of Humpback whales (Friedlaender et al., 2011) keeps the drag to a minimum to ensure movement performance and reduce loss of energy. It can swim in shallow water with good navigation and maneuverability performance, and realize the fast acceleration and deceleration of a motion. Humpback whales are huge in size, generally up to 13–15 m in length, which may be suitable as the reference of medium or large size AUVs. Above all, the bionic shape design is one of the important means to realize drag reduction and navigation performance improvement of underwater vehicles, especially for the AUVs with a high speed.

On the other hand, in order to reduce the drag of a designed shape, previous scholars have proposed some optimization methods. The traditional shape optimization methods mainly rely on the designer’s experience or the computational fluid dynamics (CFD) software. Alvarez. et al. (2009) proposed a first-order Rankine panel method to optimize the hull shape of an AUV in the operating conditions near a free surface. The CFD method can obtain the hydrodynamic parameters under the design condition without making the physical model of the underwater vehicle, which has the ascendancy of reducing the cost of time and money for each case. It is painstaking for CFD to automatically adjust the main parameters and conduct analysis on each case to obtain an ideal shape. Even there is a very slight change of the shape parameters, the process of modelling, meshing and numerical calculation of the AUV model in CFD software need to be reworked. Hence, the automatic optimization technique has important application value to avoid the drawbacks of a large workload and low efficiency of optimization with CFD.

For researchers and engineers, surrogate models (Gan et al., 2016) is a preferable method to overcome these shape optimization problems by using CFD (Crombecq et al., 2011). Studies on procedural design have been conducted by some researchers. Tang et al. (2020) optimized the hull shape only with the drag as the optimization factor by combining the multi-island genetic algorithm (MIGA) with the particle swarm optimization (PSO) method. With the maximum gliding range as the optimization target, Sun et al. (2017) optimized the shape parameters of a underwater glider with blended wing by using the genetic algorithm which has combined with Kriging method. In order to reduce drag of a submarine, Song et al. (2013) built a surrogate model of the drag with the submarine shape parameters based on the Kriging model, by applying the Latin hypercube design(LHD) method to obtain the sample points. Yang et al. (2011) solved the shape optimization problem by the response surface methodology (RSM) and MIGA considering drag and displacement volume as the optimization factors.

In order to reduce the calculate time for the shape optimization with multiparameter, a hybrid optimization model was proposed by Sun and Wang (2012) to optimize the structure of ships, which integrates a support vector machine (SVM) and genetic algorithm (GA). Artificial intelligence algorithm provides a new method for hydrodynamic calculation and optimization (Ghalandari et al., 2019; Taormina & Chau, 2015). Ghalandari et al. (2019) optimized the blade of a rig by comprising the genetic algorithm, artificial neural networks and design of experiments. Salih et al. (2019) developed an adaptive mesh refinement (AMR) algorithm to simulate the fluid flow around thin object and determine the computational cost. Shamshirband et al. (2020) combined the ant colony optimization algorithm with CFD data to anticipate the flow characteristics.

In the process of shape dimension design, it is impossible to test all the cases in the design space, making it necessary to select a certain number of sample points to reasonably represent the entire design space. The design of experiments is a sample point selection strategy, which can improve the rationality of the spatial distribution of sample points, and improve the data accuracy of the surrogate model by reducing the influence of test errors. When the number of test samples is limited, the experimental design method based on the optimization criterion can save more calculation time and obtain a certain optimal result, revealing the influence of different experimental factors on the results.

However, for complex engineering optimization problems with multiple design variables, the above method will require considerable computing resources and has a low design efficiency. The optimization of designed shape for AUV using surrogate models can greatly improve the efficiency of designers. The surrogate model has a
higher computational efficiency for the shape optimization with multiple objects. The RSM generally expresses the objectives and constraints by simple functions, such as polynomials which is fit for the common nonlinear problems. But the order of the equations for the RSM plays an important role for the data prediction accuracy and robustness of that model. The expression of the Kriging model is implicit, which requires more time to construct and improve the accuracy of the model (Kim et al., 2009). The RBF model is suitable for the highly nonlinear problems, which needs quantities of sample points (Gao et al., 2012). Since the AUV shape has many parameters and different optimization objectives, the shape optimization model is often nonlinear. On the other hand, in view of computational efficiency and workload, it is impossible to obtain a large number of sample points to build a mathematic model for the shape optimization. So it is necessary and valuable to choose or design a suitable surrogate model which is applicable to the above restrictions. Considering the above, a reasonable choice among different optimization methods may effectively improve the calculation accuracy, according to the degree of non-linearity of different optimization objectives.

In order to realize the long-distance navigation of AUV with limited energy, this paper proposes an innovative bionic shape that is much similar to that of humpback whales. The Latin hypercube sampling method is used to determine the sample points to establish the surrogate model. Then, considering the commonly nonlinear relation between drag or displacement volume of AUV and physical geometric parameters of shape, and the limited sample points to build the optimization model, RSM is chosen to build the surrogate model of drag or volume using hydrodynamic results from cases designed by TPLHD. Finally, the BHS optimization is carried out under the constraints of length and displacement volume, providing technical support for the AUV with low drag, large volume, and long voyage (Figure 1).

This work is arranged as follows. Section 2 presents the design of bio-inspired hull shape (BHS). Section 3 presents an optimal design of the shape based on the surrogate model. Section 4 describes the numerical simulation validation, experimental validation and discussions. Section 5 concludes the whole paper.

2. Design of BHS

2.1. Geometry definition of the hull shape

Comparing the shape feature of Schemes 1–8 in Figure 10 and Table 8 and other underwater vehicles (Alvarez et al., 2009; Gao et al., 2016; Hobson et al., 2012; Honaryar & Ghiasi, 2018; Li & Feng, 2001; McPhail, 2009; Nesteruk et al., 2014; Zhang et al., 2017), three main conclusions can be obtained: (a) Most of the shapes, which consist of three parts: bow part, middle part and stern part, is mostly revolving and a few are polygonal. (b) The outline of bow and stern are mostly Myring-type. (c) The cross-section of the middle section is mostly round, ellipse or square.

Humpback whales have a relatively small head with a wide snout and a large mouth. Its cross-section is similar to an ellipse, and the dimensions on both sides are larger than the upper and lower dimensions. Inspired by the shape of the humpback whale(Figure 2), this paper designs an innovative hull shape for AUV with a good streamlined body and reasonable volume utilization. The shape model is defined with a bow and a tail section, without a middle section to connected them, which can make the junction of the bow and tail streamlined, just like a humpback whale(Figure 2). To improve the space utilization of the tail, the bow and tail are designed to be symmetrical. Considering its good hydrodynamic performance and easy manufacture, the Myring-type streamline is popularly used in the body shape design of underwater vehicles, such as the Autonomous Underwater Vehicle 6000 (McPhail, 2009). Thus, it is selected to describe the shape of the humpback whales. The cross-section

**Figure 1.** Typical shape of Humpback whales.
of BHS is an ellipse. Figure 2 shows the shape and its parametric model. The bow is described as:

\[
\begin{align*}
  r_x(x) &= \frac{x_1}{2} \left[ 1 - \left( \frac{x}{a} \right)^2 \right] \frac{1}{n_1} \\
  r_y(x) &= \frac{x_2}{2} \left[ 1 - \left( \frac{x}{a} \right)^2 \right] \frac{1}{n_2} (x \in [-a, a]) \\
  \left( \frac{z_L}{r_x(x)} \right)^2 + \left( \frac{y_L}{r_y(x)} \right)^2 &= 1
\end{align*}
\]

where \( x_1 \) is the length of the major axis of the maximum elliptical cross section in plane \( yOz \), \( x_2 \) is the length of the minor axis of the maximum elliptical cross-section in plane \( yOz \), \( n_1 \) and \( n_2 \) are the parameters that control the curvature of a curve, \( r_y(x) \) and \( r_x(x) \) are the \( y \)-axis coordinate and the \( z \)-axis coordinate of a bow at the position \( x \), respectively, \( z_L \) and \( y_L \) are the coordinates of the point on the contour line intersected by the external surface of shape and the plane \( x = L \) parallel to the plane \( yOz \).

2.2. Optimization target and decision variables

Influenced by different factors such as sailing range and sensors payload, the body length of AUV ranges from several meters to tens of meters and displacement ranges from dozens of kilograms to dozens of tons. The length of most small and medium-sized AUVs are within 5 m, and the maximum cross-sectional length is less than 1.0 m (Gao et al., 2016; Hobson et al., 2012; Li & Feng, 2001; McPhail, 2009; Nesteruk et al., 2014). In this paper, the length of BHS \( L_{AUV} \) is kept at 4.9 m and the maximum size of the cross-section is 1 m. Owing to the limited energy load of AUV, reducing the drag of the hull is a good way to improve the range of AUV. When AUV sails underwater, there is a pressure difference between the bow and tail part. The curvature of the body streamline can be adjusted by changing the value of \( n_1 \) and \( n_2 \) to make the hull pressure tends to be more flatter. Therefore, drag is taken as the first optimization target for the BHS. To guarantee sufficient space of BHS for loading the control system, energy system, communication system and sensors, displacement volume is taken as the second optimization factor, which can also be expressed by the volume of the shape. As seen in Figure 2, the volume of BHS is obtained by calculating a definite integral of the body section area. It can be expressed as

\[
V_{AUV} = 2 \int_0^a S(x_0) dx_0
\]

where \( S(x_0) \) is the area of the body section at the plane \( x = x_0 \). Because the shape of the cross-body section of BHS is an ellipse, \( S(x_0) \) can be computed as:

\[
S(x_0) = \pi r_y(x_0) r_x(x_0)
\]

In order to ensure the rationality of the shape parameters, design variables and their ranges were determined after investigating the dimensions of the existing underwater vehicles and estimating the dimensions of the internal components (Alvarez et al., 2009; Gao et al., 2016; Hobson et al., 2012; Honaryar & Ghiasi, 2018; Li & Feng, 2001; McPhail, 2009; Nesteruk et al., 2014; Zhang et al., 2017) (Table 1).

3. Optimal shape design of BHS based on the surrogate model

To improve the efficiency of the experiment design, a surrogate model is established to optimize the shape of BHS by using RSM, during which the TPLHD is adopted to obtain sampling points. Figure 3 shows the specific optimization procedure. Firstly, the design variables, their ranges and the optimization targets were defined. Secondly, TPLHD is used to determine the sampling values of each variable. After that, the 3-D model of each case was designed based on the sampling data, and the response values were obtained through numerical simulation. Finally, the cubic RSM was selected to obtain the approximate model and complete the optimal design.

| Design variable                  | Notation | Minimum | Maximum |
|----------------------------------|----------|---------|---------|
| Maximum width in the horizontal plane \( yOy \) | \( x_1 \) | 0.7 m   | 1 m     |
| Maximum height in the vertical plane \( yOz \) | \( x_2 \) | 0.5 m   | 0.7 m   |
| Shape factor of horizontal midsection profile | \( n_1 \) | 1       | 3       |
| Shape factor of vertical midsection profile | \( n_2 \) | 1       | 3       |
Conventional Latin hypercube design (Mckay et al., 1979) is commonly used for experiment design (Iman & Conover, 1980), which can obtain a certain number of sampling points and guarantee the orthogonality of any two sampling point. However, the randomness of sample point selection is relatively strong, which leads to poor space-filling quality. TPLHD is a relatively fast optimal Latin hypercube sampling method with high space-filling quality (Ye et al., 2000; Zhu et al., 2012) and can avoid the impact of sample randomness effectively. A sampling example of seventeen points in two dimensions (namely $17 \times 2$) by TPLHD is briefly explained with the following four steps.

**Step 1**: Calculate the number of blocks $n_d$ divided into equal parts for each dimension.

$$n_d = \left\lceil \left( \frac{n_p}{n_s} \right)^{\frac{1}{n_v}} \right\rceil$$

$$n_p^* = n_d^{n_v} \times n_s$$  \hspace{1cm} (4)  

where $[*]$ means to round up, $n_p$ represents the value of the point scale of the demand LHD, $n_s$ represents the point scale of the initial design, $n_v$ represents the point scale of initial seed, and $n_v$ represents the number of variables.

In the example of $17 \times 2$ TPLHD, it can be obtained that the initial number $n_s$ of seeds is 2, the number of blocks $n_d$ is 3, and $n_p^*$ is 18.

**Step 2**: Design the initial seed distribution. The same number of initial seeds will eventually get completely different sampling results due to different distributions. As shown in Figure 4(a), the initial seeds are placed in the block near the origin according to (Alvarez et al., 2009; Viana et al., 2010).

**Step 3**: Based on the idea of translation propagation, the sample points are translated $(n_d - 1)$ times in each dimension. When the sample points are moved, the new points will be a new part of the design space. In order to avoid taking two sample points in the same interval, it is necessary to offset each translation points. Figures 4(b,c) show the propagation process of the $17 \times 2$ example. Based on (Sun et al., 2020), the same displacement vector in each translation for the initial sampling point is adopted to improve space-filling quality.

**Step 4**: The experiment design completes when the number of existing sample points reaches the required value. The redundant points far away from the design space center, including the spacing of these points, shall be discarded, when the number of the existing sample points is larger than the requirements. Finally, sample points are resized to fill the entire design space. Figure 4(d,e) shows the process of discarding redundant sample points, and the desired $17 \times 2$ TPLHD is obtained.

In the optimal design for BHS, TPLHD with four-dimensional design space is used to design the experiment. The number of sample points is set to 60 ($n_p = 60$) to improve the predict accuracy of the surrogate model. Since it is not possible to directly display the sampling results in a four-dimensional design space, the sample points are mapped to the plane $x_1-x_2$, $x_1-n_1$ and $x_1-n_2$ planes (Figure 5).

**3.2. Hydrodynamic simulation**

Many kinds of research have focused on CFD to accurately calculate the drag of underwater vehicles, such as (Gao et al., 2016; Parfitt & Vincent, 2005; Sun et al., 2017; Tang et al., 2020; Zhang et al., 2017). This part chooses ANSYS Fluent to simulate the BHS drag, whose main body length is $L_{AUV}$. The water inlet boundary is the velocity inlet and the water outlet boundary is the pressure outlet. The distance from the water inlet boundary to the head of BHS is about $3L_{AUV}$. The distance from the water outlet boundary to the tail of the underwater vehicle is about $5L_{AUV}$. The radius of the simulated water boundary is 10 times larger than the maximum width of the BHS. In the process of numerical simulation, the speed of the water current is set to 5 m/s.

When the Reynolds number is between $8.85 \times 10^6$ and $3.967 \times 10^7$, (Peng, 2019) uses the $k-\omega$ SST turbulence model to carry out numerical analysis of the sailing drag of the international standard model (SUBOFF-2). The simulation data are basically consistent with that of Lin et al. (2018), and compared with the test data under the same conditions, the minimum relative error is 2.25%, and the average error is 4.33%. The Reynolds number of
the BHS model can be calculated as:

$$Re = \frac{\rho v L_{AUV}}{\mu} = \frac{998.2 \text{kg/m}^3 \times 5 \text{m/s} \times 4.9 \text{m}}{1.005 \times 10^{-5} \text{Pa} \cdot \text{s}}$$

$$= 2.433 \times 10^7$$

where, $\rho$ is the density of the water, $v$ is the cruising speed of the AUV, and $\mu$ is the viscosity of the water at 20°C.

When the cruising speed of the AUV with BHS changes from 2 m/s to 5 m/s, the Reynolds number ranges from $9.973 \times 10^6$ to $2.433 \times 10^7$. In this paper, the $k - \omega$ SST turbulence model is also used to calculate the hydrodynamics of BHS. With the refinement of the grid by decreasing the grid size and increasing number of grid cells, the spatial discretization error should be asymptotically zero to exclude the computer rounding error. Grid independence verification is a necessary step to obtain accurate results based on CFD. Case No. 20 in the samples is randomly selected as the simulation object. The specific procedure is described as follows. First of all, the height
and \( Y = [y^{(1)}, y^{(2)}, \ldots, y^{(60)}]^T \), respectively. Then the quadratic RSM is used to explain the construction process. The quadratic polynomial function is \([1, x_1, x_2, \ldots, x_n, x_1^2, x_1x_2, \ldots, x_1x_n, \ldots, x_n^2]^T\).

Substituting 60 groups of design variables and the corresponding drag into Equation (6), an equation set containing 60 equations can be obtained:

\[
Y = A\beta
\]

(7)

\[
A = \begin{bmatrix}
P_1(x^{(1)}) & \cdots & P_L(x^{(1)}) \\
\vdots & \ddots & \vdots \\
P_1(x^{(N)}) & \cdots & P_L(x^{(N)})
\end{bmatrix}
\]

(8)

\[
\beta = (A^T A)^{-1} A^T Y
\]

(9)

where \( A \) represents the basis function matrix of 60 samples, and \( \beta = [\beta_1, \beta_2, \ldots, \beta_L] \) represents the undetermined coefficient matrix.

Substituting \( \beta \) into Equation (7), the drag approximation function based on quadratic RSM is expressed as:

\[
\tilde{D} = 177.2388 + 91.9367x_1 - 425.9272x_2
- 22.0926n_1 - 15.5818n_2 + 0.5208x_1^2 \\
+ 94.164x_1x_2 + 25.8538x_1n_1 + 20.6404x_1n_2 \\
+ 388.8819x_2^2 + 32.4119x_2x_3 \\
+ 21.0438x_2x_4 - 2.1191x_3^2 + 4.8103x_3x_4 \\
- 1.7660x_4^2
\]

(10)

Then, the approximate models of drag and volume based on quadratic RSM and cubic RSM are obtained respectively. The coefficient of determination \( R^2 \) and root mean squared error \( R_{MSE} \) are usually used for evaluating the accuracy of RSM, which belongs to a fitting surrogate model. The \( R^2 \) and \( R_{MSE} \) are shown as follows:

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \tilde{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]

(11)

\[
R_{MSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \tilde{y}_i)^2}
\]

(12)

where \( y_i \) is the \( i \)th response value, \( \tilde{y}_i \) is the \( i \)th predicted value, \( \bar{y} \) is the mean value of all \( y_i \), and \( N \) is the number of samples.

The closer the value of \( R^2 \) is to 1 and the value of \( R_{MSE} \) is to 0, the higher the fitting accuracy of the surrogate model is. Tables 3 and 4 present the fitting accuracy of surrogate models for drag and volume obtained by quadratic RSM and cubic RSM respectively.
It can be seen from the values of $R^2$ and $R_{MSE}$ that the surrogate model based on cubic RSM has better fitting accuracy for drag and volume than that based on quadratic RSM. To further verify the established surrogate model based on RSM, another surrogate model based on radial basis function (RBF) is also established obtained as a comparison. The specific process of RBF is performed by using a radial basis function as a transfer function to construct an approximate model through linear weighted sum method. The mathematical equation of RBF is

$$\tilde{y}(x) = \sum_{i=1}^{N} \lambda_i \phi(||x - x^i||) + \mu$$  \hspace{1cm} (13)

where $\tilde{y}(x)$ is the output response function, $\lambda_i$ is weight coefficient, $r = ||x - x^i||$ is Euclidean distance between the predicted point and the $i$th sample point, $\phi(r)$ is basis function, and $\mu$ is either a polynomial model or a constant value.

A muti quadric function (Soleymani et al., 2018) is used as the basis function of the surrogate model based on RBF, which is

$$\phi(r) = (r^2 + c^2)^{1/2}$$  \hspace{1cm} (14)

where $r$ represents Euclidean distance and $c$ represents shape parameter.

According to the calculation method of shape parameter given in references (Fasshauer, 2002; Viana et al., 2010), $c$ is calculated by $c = 2/\sqrt{n}$ and $\mu$ is calculated by $\mu = 1/n \sum_{i=1}^{n} y_i$.

Next, substituting 60 groups of design variables and corresponding responses in the samples into Equation (13), the construction of the surrogate model based on RBF is shown clearly as

$$Y = \Phi\lambda$$ \hspace{1cm} (15)

$$\lambda = (\Phi^T\Phi)^{-1}\Phi^T(Y - \mu)$$ \hspace{1cm} (16)

where $\lambda$ is the undetermined coefficient matrix, and $\Phi$ is calculated by

$$\Phi = \begin{bmatrix}
\phi(||x^1 - x^1||) & \phi(||x^1 - x^2||) \\
\phi(||x^2 - x^1||) & \phi(||x^2 - x^2||) \\
\vdots & \vdots \\
\phi(||x^{60} - x^1||) & \phi(||x^{60} - x^2||) \\
\vdots & \vdots \\
\phi(||x^1 - x^{60}||) & \phi(||x^2 - x^{60}||) \\
\end{bmatrix}$$ \hspace{1cm} (17)

Substituting $\lambda$ into Equation (15), the approximation function based on RBF can be achieved, as shown in the Appendix. RSM is a kind of fitting surrogate model, whose accuracy can be evaluated with $R^2$ and $R_{MSE}$. Unlike RSM, RBF is a kind of interpolating surrogate model, whose accuracy can be evaluated by cross-validation or increasing off-design points. Thus, five validation points based on Latin Hypercube are selected as additional sample points.

Figure 7 shows the measured values and the predicted values of drag and volume, respectively. The specific data of $R^2$ and $R_{MSE}$ are shown in Tables 5 and 6. The verification results of additional test points prove that the cubic RSM model has a good approximation ability in terms of drag and volume. Therefore, cubic RSM is selected to construct the surrogate model of drag and volume. The cubic RSM is as follows (further details in the Appendix).

$$\tilde{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 n_1 + \beta_4 n_2 + \beta_5 x_1^2$$

$$+ \beta_6 x_1 x_2 + \beta_7 x_1 n_1 + \beta_8 x_1 n_2 + \beta_9 x_2^2 + \beta_{10} x_2 n_1$$

$$+ \beta_{11} x_2 n_2 + \beta_{12} n_1^2 + \beta_{13} n_1 n_2 + \beta_{14} n_2^2 + \beta_{15} x_1^3$$

$$+ \beta_{16} x_1 x_2^2 + \beta_{17} x_1^2 n_1 + \beta_{18} x_1^2 n_2 + \beta_{19} x_1 x_2^2$$

$$+ \beta_{20} x_1 x_2 n_1 + \beta_{21} x_1 x_2 n_2 + \beta_{22} x_1 n_1^2 + \beta_{23} x_1 n_1 n_2$$

$$+ \beta_{24} x_1 n_2^2 + \beta_{25} x_2^3 + \beta_{26} x_2^2 n_1 + \beta_{27} x_2^2 n_2 + \beta_{28} x_2 n_1^2$$

$$+ \beta_{29} x_2 n_1 n_2 + \beta_{30} x_2 n_2^2 + \beta_{31} n_1^3 + \beta_{32} n_1^2 n_2$$

$$+ \beta_{33} n_1 n_2^2 + \beta_{34} n_2^3$$  \hspace{1cm} (18)

Taking both the drag and volume as optimization factor in the design of BHS is a multi-objective optimization problem. Pareto (Stanoević & Glover, 2020) proposed the concept of non-dominated set in multi-objective optimization problems in 1982. Assume that there are two solutions: $S_1$ and $S_2$. When $S_1$ is better than $S_2$ for all targets, $S_1$ dominates $S_2$. If $S_1$ is not dominated by other solutions, then it is called a non-dominated solution or a Pareto solution. It can be seen from the results of the
RSM that variation trends of drag with the input variables are more similar to that of volume. As shown in Figure 8, approximate function images of drag and displacement volume are obtained when some variables have fixed values, where the nonlinear characteristics between design variables and output responses can be seen intuitively.

Choosing the minimum drag and the maximum displacement volume as the optimization targets belong to Pareto optimality. To improve the efficiency of optimization and consider the internal volume requirement, the volume is set to 1.6 m$^3$ to carry out the optimization of shape parameters for low drag.

\[
\begin{align*}
\min(D) \\
1.5995 m^3 < V < 1.6004 m^3
\end{align*}
\]  

where $D$ represents the drag of BHS at a speed of 5 m/s, and $V$ represents the volume of BHS.

According to the approximate function obtained based on cubic RSM, the data of input variables are obtained, which meets the volumetric requirement in the design space. According to the obtained data set, the optimal solution is achieved based on the drag approximation function.

The optimal solution and some typical solutions are shown in Table 7. It can be seen that several groups of design variables meet the volumetric requirement of 1.6 m$^3$, and No. 1 in Table 7 has the least drag in about 1.7 million groups of data. Figure 9 illustrates the outline drawing of the optimization result.

### 4. Validation and analysis by numerical simulation

#### 4.1. Numerical simulation validation

For verifying the hydrodynamic advantages of BHS and the optimization using cubic RSM in this paper, the drag computations for BHS and eight typical hull shapes from existing typical or bionic AUV shapes are performed and compared, under conditions of similar volume, wet surface area, body length and attachments. The typical shapes include revolving shape, non-revolving shape, raindrops shape and bionic shapes. The streamlined shape includes Myring-type, Spline-curve-type and NACA-type. Based on the above rules, eight different shapes were obtained to compare with the BHS. The details of these shapes are shown in Figure 10 and Table 8. Scheme 8 is the optimized bionic shape proposed in this paper.

As can be seen in Figure 10, the shapes of Scheme 1, Scheme 2, Scheme 3 and Scheme 7 are revolving. The shape of Scheme 7 is similar to the waterdrop shape. The shape of Scheme 3 is most similar to Scheme 2, but instead of having a curved surface, the bow of Scheme 3 is a flat one. The shapes of Scheme 2, Scheme 3, Scheme 4 and Scheme 5 contain a middle section. The difference among them is that the cross section of Scheme 4 is elliptical, and the cross-section of Scheme 5 is square. The space utilization rate of the square section vehicle is excellent. The shape of Scheme 6 is most similar to
that of Scheme 1, except that the cross-section of the former is an ellipse. The shape of Scheme 8 with a cross-sectional shape of NACA0020 is taken from the catfish profile (Honaryar & Ghiasi, 2018), which has good stability. Besides, all shapes are equipped with the same schematic propeller, lifting lugs, antenna and rudders.

According to Figures 11 and 12, it can be seen that the nine schemes have similar volume and wet surface area. The viscous drag of the shapes involves friction drag and pressure drag. When the schemes are at the same speed and angle of attack (AOA), the order of viscous drag from small to large is: Scheme 9, Scheme 7, Scheme 1, Scheme

Figure 8. Approximate function images of drag and volume. (a). The influence of $n_1$ and $n_2$ on drag and volume, respectively. (b). The influence of $x_1$ and $x_2$ on drag and volume, respectively.
Figure 8. Continued.

Table 7. The optimal solution and some typical solutions.

| No. | $x_1$ (mm) | $x_2$ (mm) | $n_1$ | $n_2$ | Drag (N) | Volume (m$^3$) |
|-----|------------|------------|-------|-------|----------|----------------|
| 1   | 930        | 700        | 1.71  | 1.72  | 287.25   | 1.600          |
| 2   | 1000       | 600        | 2.00  | 2.70  | 308.97   | 1.600          |
| 3   | 956        | 600        | 3.00  | 2.55  | 317.43   | 1.600          |
| 4   | 870        | 653        | 2.73  | 3.00  | 313.38   | 1.600          |

2, Scheme 8. Scheme 2, Scheme 4, Scheme 5 and Scheme 6 have similar viscous drag values. When both the speed and AOA are the same for the nine schemes, the frictional drag of different shapes is basically the same, but there is a large difference in pressure drag, and the Scheme 9 has the smallest pressure drag than other shapes.

(b). The influence of $x_1$ and $x_2$ on drag and volume, respectively.
Furthermore, known from Table 7 and Figure 12, it can be concluded that the addition of attachments to the shapes, such as propeller, lifting lugs, antenna, rudder, etc, will significantly increase their viscous drag.

### 4.2. Experimental verification

For verifying the correctness of the hydrodynamic data and shape optimization results achieved in the simulation analysis, a scaled-down model with a ratio of 1:2 to the...
Table 8. Shape parameters and linetypes.

| Scheme | Middle part | Cross-section shape | Linetype of bow/tail | Total volume (m³) | Maximum length of the largest cross-section (mm) |
|--------|-------------|---------------------|---------------------|------------------|---------------------------------|
| 1 (Eriksen et al., 2001) | Not Contain | Circle | Myring/Myring | 1.593 | 800 |
| 2 (McPhail & Pebody, 2009; Wadhams, 2012) | Contain | Circle | Myring/Myring | 1.681 | 750 |
| 3 (Jin et al., 2018) | Contain | Circle | Myring(Flat)/Myring | 1.629 | 700 |
| 4 (Lee et al., 2005) | Contain | Ellipse | Myring/Myring | 1.659 | 900 |
| 5 (Boeing, 2020) | Contain | Square | Myring/Myring | 1.636 | 799 |
| 6 (Lee et al., 2005) | Not Contain | Ellipse | Spline curve/Spline curve | 1.636 | 893 |
| 7 (Honaryar & Ghiasi, 2018) | Not Contain | NACA0040 | NACA0020/NACA0020 | 1.664 | 1000 |
| 8 (Honaryar & Ghiasi, 2018) | Not Contain | Ellipse | Myring/Myring | 1.662 | 930 |

Figure 11. The volume and wet surface area of each scheme.

Original is manufactured with FRP material, which avoids large deformation under the effect of a large hydrodynamic force. The geometric parameter accuracy of the shape model is kept at ±0.3 mm, and its outside surface is kept smooth by spraying a coat of paint. Its rigidity is large enough to prevent obvious deformation. In order to reduce the affeccion of the surface water waves on that force sensor, the shape model is placed at about 2.0 m under the water surface and 2.0 m above the bottom in the experiment for the drag measurement. A six-axis force measuring sensor is installed in the hull and used to measure the hydrodynamic force. Some rods are added between the sensor and the hull to reduce the shaking of the hull relative to the sensor. The ranges of the sensor in the measurement of lift and drag are 800 N and 800 N, respectively. The resolution of the force sensor is 0.25% of the full scale. The uncertainty of the force measurement is below 3.2 N in the current study. The Reynolds number of the scaled-model can be calculated as

\[
Re = \frac{\rho v L^2}{\mu} = \frac{998.2 \text{kg/m}^3 \times 2.2 \text{m/s} \times 2.45 \text{m}}{1.005 \times 10^{-3} \text{Pa} \times \text{s}} = 5.353 \times 10^6
\]  

(21)

Figure 12. Simulation analysis and comparison of navigation drag of different schemes.
Figure 13. Installation of the scaled-down BHS model on the trailer.

The size of the towing tank is 108 m long, 7 m wide, and 3.5 m tall. The steady speed range of the trailer system is 0.1–4.5 m/s with an error rate of 0.5%. There is a rectangle hole on the left side of the model. When the model is installed on the towing, the center axis of the rectangle hole is perpendicular to the horizontal plane. The model is connected to the trailer through a restraining frame above the sensor (Figure 13.). After installation, the AOA of the model can be adjusted through a flange. The design of the restraining frame ensures that the underwater depth of the model is 3.7 times greater than the maximum diameter of the model.

Figure 14 is the drag of the scaled-down BHS obtained by the experimental test at different sailing speeds and AOAs. At the same sailing speed, the drag of BHS increases with the increase of AOA. The changing trend of drag with AOA and speed obtained by CFD is basically consistent with the results measured from the experiment. When the velocity of BHS is larger, the change trend and magnitude of the measured hydrodynamic force are much closer to those obtained by simulation. However, when the AOA is small, the measured hydrodynamic force will deviate greatly from the simulated value. At the same AOA and speed, the drag value obtained by the test is larger than that obtained by simulation, but the average relative error is below 4.09%.

4.3. Analysis of errors between simulations and experiments

The error analysis was performed to compare the simulation and experimental results. As shown in Figure 14, there are noticeable errors between the hydrodynamic forces obtained by the simulations and experiments. When the speed of BHS is small, the relative errors of drag between simulation and test results is greater, which can be attributed to the following four:

1. The viscosity and density of water are standard values in the simulation, which, however, cannot be ensured in the experiments.
5. Conclusion

This paper proposes an innovative hull shape inspired by the appearance shape of a humpback whale for AUV and conducts the optimization of BHS by surrogate model technology. The equation for BHS is established based on the Mrying shape equation and the ellipse equation through the analysis and summary the feature of the existing underwater vehicle’s shape. The design parameter of the BHS is optimized with the limitation of the objective functions of the hull drag and the volume. In the optimization process, by using RSM and TPLHD, we obtained the value of the four parameters of BHS, which can make the BHS has the minimum sailing drag under the condition of a certain length (4.9 m) and drainage volume (1.6 m³). In order to verify the optimization results of BHS, the drag computations by CFD for BHS and other eight typical hull shapes of existing typical or bionic AUVs are performed for comparison under conditions of similar volume, wet surface area, body length and attachments. The results show that the drag of BHS with attachments is the smallest among the nine shapes. At the same speed and AOA, the BHS has outstanding advantages with the smallest pressure drag, compared with the other eight shapes. Furthermore, a scale model was designed, manufactured and experienced in a towing tank to verify the accuracy of simulation results. Comparing the towing experiment results with the numerical simulation by CFD, the average relative error of the drag is no more than 4.09% at each speed, which further proves the accuracy and effectiveness of simulated hydrodynamics. Therefore, the proposed BHS and the optimal method are effective to reduce the drag of an AUV. Compared with common axisymmetric shapes, the AUV with BHS can have less energy consumption than the other shapes and is thus highly suitable for long-distance tasks.

Although some achievements have been made in this paper, there are still some limitations. The AUV has many underwater movement forms, such as translation, rotation, acceleration and direction changing. Considering that the motion of AUV is mainly direct navigation, this paper only takes the direct navigation drag as the optimization objective and the volume of the vehicle as the constraint to optimize the parameters of the proposed BHS. In the future, AUV’s underwater motion of rotation, acceleration and direction changing will be taken into consideration to optimize the shape of BHS. The AUV hydrodynamics will be analyzed and optimized considering the layout and size of appendages, such as rudder, lifting lugs and thrusters. The BHS manoeuvrability will be studied to enlarge the sailing distance, and the attachments will be considered in the optimization, which has an uncertain influence on the endurance ability. After that, an AUV prototype using this BHS will be designed and manufactured to test sailing performance in a real marine environment.

Disclosure statement

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**Appendix**

The approximate functions of drag and volume based on cubic RSM are given as follows:

\[
\bar{D} = -977.3165 + 2905.8311x_1 + 11.1272x_2 + 286.2766n_1 + 69.8130n_2 - 3063.5910x_1^2 - 1798.5940x_1x_2 - 9.8608x_1n_1 + 362.2331x_1n_2 + 3363.7037x_2^2 - 666.7350x_2n_1 - 562.8802x_2n_2 - 25.0063n_1^2 - 28.8107n_1n_2 - 10.2953n_2^2 + 1125.6562x_1^3 + 1320.1363x_1^2x_2 - 20.6261x_1^2n_1 - 248.2159x_1^2n_2 - 171.5460x_1x_2^2 + 64.9377x_1x_2n_1 - 139.6582x_1x_2n_2 - 2.7438x_1n_1^3 + 19.3787x_1n_1n_2 + 28.8090x_1n_2^2 - 2879.9602x_2^3 + 438.3233x_2^2n_1 + 618.2336x_2n_1^2 + 30.1567x_2n_1n_2 - 6.2340x_2n_2^2 - 4.7806x_2n_2^3 + 1.1213n_1^3 - 0.6667n_1n_2^2 + 6.0823n_1n_2^2 - 4.4219n_2^3
\]

\[
\bar{V} = -0.6035 - 1.0594x_1 + 4.3786x_2 + 0.0083n_1 - 0.0680n_2 + 0.6442x_1^2 - 2.9656x_1x_2 + 0.0680x_1n_1 + 0.1115x_1n_2 + 9.3345x_2^2 + 0.2020x_2n_1 + 0.5548x_2n_2 - 0.0372n_1^2 + 0.0350n_1n_2 - 0.0663n_2^2 - 0.3843x_1 - 0.9802x_1^2 + 0.0654x_1^2n_1 - 0.0417x_1n_2^2 + 0.1882x_1x_2 + 0.1114x_1x_2n_1 + 0.3612x_1x_2n_2 - 0.0481x_1n_2^2 + 0.0296x_1n_1n_2 - 0.0485x_1n_2^2 + 5.5178x_2^3 - 0.3585x_2^2n_1 - 0.3563x_2n_1^2 + 0.0351x_2n_1n_2 + 0.0226x_2n_1n_2 - 0.0776x_2n_2^2 + 0.0092n_1^3 + 0.0021n_1n_2 - 0.0154n_1n_2^2 + 0.0240n_2^3
\]
The approximate functions of drag and volume based on quadratic RSM are given as follows:

\[
\tilde{D} = 177.2388 + 91.9367x_1 - 425.9272x_2 - 22.0926n_1 \\
- 15.5818n_2 + 0.5208x_1^2 + 94.1643x_1x_2 + 25.8538x_1n_1 \\
+ 20.6404x_1n_2 + 388.8819x_2^2 + 32.4119x_2x_3 \\
+ 21.0438x_2x_4 - 2.1191x_3^2 + 4.8103x_3x_4 - 1.7660x_4^2
\]

\[
\tilde{V} = 0.1685 + 0.4884x_1 - 0.7318x_2 + 0.0274n_1 - 0.0448n_2 \\
+ 0.0135x_1^2 + 2.6190x_1x_2 + 0.1084x_1n_1 + 0.1008x_1n_2 \\
+ 0.1326x_2^2 + 0.1425x_2x_3 + 0.1174x_2x_4 - 0.0373x_3^2 \\
+ 0.0205x_3x_4 - 0.0361x_4^2
\]