Multi-Objective Optimization of Gatling gun Tripod Based on Mesh Morphing and RBF Model

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Abstract: - Large elastic deformation of Gatling gun tripod during the shooting process is an important factor affecting the firing accuracy. Mesh morphing and approximate model technique are comprehensively applied to the multi-objective optimization of gun tripod for improving its rigidity aiming at this problem. After finite element model of tripod is established, mesh morphing technique is utilized to define shape variables. The traditional dimension variables together with the shape variables defined by utilizing mesh morphing technique are combined to act as the design variables. Then optimal variables are screened out by Plackett-Burman design. Hammersley sampling is employed to generate uniformly distributed sampling points for fitting high-precision RBF model. Multi-Objective Genetic Algorithm is adopted to perform the optimization in which the longitudinal stiffness and transverse stiffness of tripod are defined as the objective functions while the mass of tripod leg is defined as a constraint function. The optimal solution can turn out that the longitudinal stiffness and transverse stiffness of tripod can be improved simultaneously by applying the proposed methodology to the multi-objective optimization for gun tripod.

Key-Words: - Mesh morphing; Design of experiments; RBF model; Multi-objective optimization

1. Introduction

Gun tripod is used to support gun body assembly and keep shooting stable. The performance of gun tripod has a close relationship with the performance of weapon. Good gun tripod can enhance weapon's shooting power, improve weapon's maneuverability and serviceability, while poor gun tripod would have an adverse influence on weapon's performance [1].

In the firing process, large elastic deformation of gun tripod will affect the firing accuracy of machine gun. Therefore, improving stiffness of gun tripod is an effective method to increase the firing accuracy of large caliber machine gun.

Improving the stiffness of gun tripod is an important research content in the design and optimization of machine gun. Traditional structural optimization of gun tripod is mainly intended to build simplified finite element model with beam element to study matching relation between dimension variables and gun shooting stability [2-4]. But this modeling method is restricted. Paper [5] puts forward a method to improve rigidity of gun tripod by defining and optimizing shape variables, which provide a new idea for gun tripod design. But only shape variable is considered in the research. If shape variable optimization can be combined with dimension variable optimization, the optimal solutions can be more effective. In this paper, dimension variables of wall thickness and shape variables of gun tripod leg are combined together with mesh morphing technique. Gun tripod structure is optimized using radial basis function (RBF) model and multi-objective genetic algorithm. And the rigidity of gun tripod is increased after optimization, which can improve shooting accuracy.

2 Optimization flow

Optimization strategy based on approximate model is adopted in this paper and the concrete flow is as shown in Fig.1.

(1) Analyze the initial mass and rigidity of gun tripod with finite element method.

(2) Parameterize the finite element model of gun tripod.

(3) Screen out design variables with Plackett-Burman (PB) designs.

(4) Establish proximate model with Hammersley sampling technique.

(5) Optimize the proximate model to obtain optimal solutions.

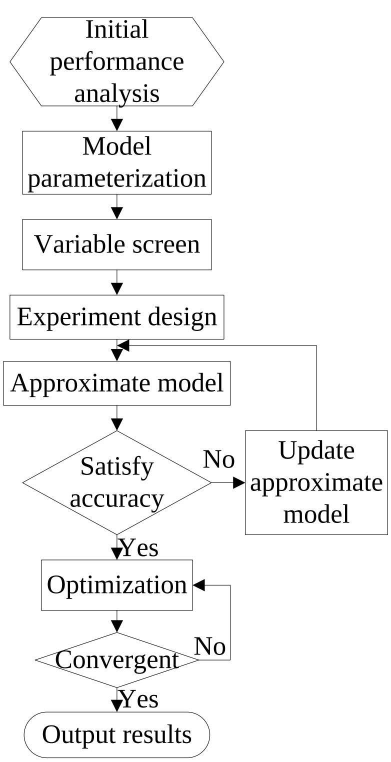


Fig.1 Optimization flow chart

3 Initial model analysis

As shown in Fig.2, a certain Gatling gun tripod is composed of rotating frame, front and back tripod leg as well as front and back spade. Three performance indexes known as the longitudinal stiffness, transverse stiffness and mass of tripod are investigated in this paper and the initial performance results are listed in Table 1. As shown in Fig.3, F_1 and F_2 are forces acting on gun tripod in longitudinal direction and transverse direction respectively. Longitudinal stiffness of tripod is defined as ratio between F_1 and displacement of force point, and transverse stiffness of tripod is defined as ratio between F_2 and displacement of force point. In Table 1, m represents mass, y_1 represents longitudinal stiffness and y_2 represents transverse stiffness.

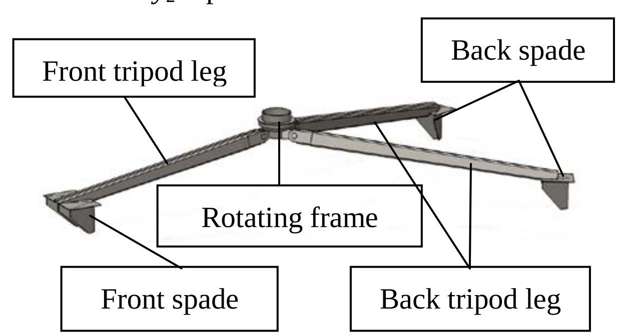


Fig.2 Gun tripod structure

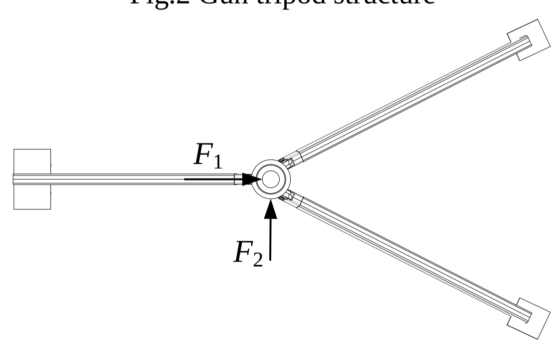


Fig.3 Tripod model for stiffness analysis

Table 1 Initial mass and stiffness of Gatling gun tripod

Parameter	Value
m/kg	4.04
y_1/(N·mm^{-1})	39361

y_2/(N·mm^{-1})	8061

4 Model parameterization based on mesh morphing

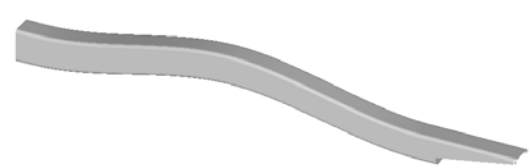
Gun tripod's rigidity and stability are determined by its structural dimensions. As the length of tripod leg has been given, wall thickness and shape of tripod can be optimized to increase its rigidity. In this paper, dimension variables of wall thickness together with shape variables of gun tripod leg are combined as design variables. Wall thickness of tripod belongs to the category of dimension variable, which is relatively easy to be implemented. Shape morphing which belongs to shape variables has been difficult to be implemented in traditional CAE optimization until the mesh morphing technique appeared. Mesh morphing technique provides an effective tool for shape optimization [6-7].

In essence, the mesh morphing in CAE model is that nodes move according to the given forms to achieve mesh translation, rotation, scaling and projection. The given forms can be mathematics form with matrix representation, or geometry form defined by objective shape [8]. In HyperMesh there are three kinds of shape morphing: morph domains, morph volume and freehand. This paper uses morph volume to change tripod's shape dimensions to define shape variables.

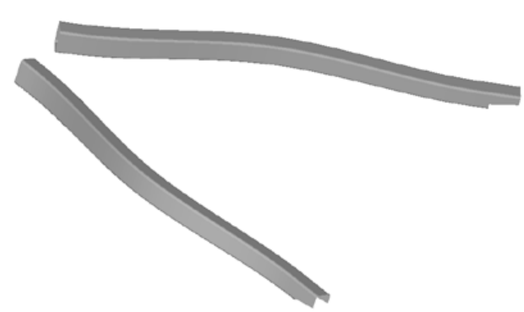
Gun tripod leg is a typical long and thin plate structure, so it can be modeled with shell element to improve computing speed and efficiency [7]. Rotating frame and spades are estimated with solid element. The structure in weld junctions between tripod legs and rotating frame as well as spades remain unchanged. Nodes in the connection location are merged. For this study, two dimension variables and nine shape variables were selected. The two dimension variables are respectively wall thickness of front tripod leg x_{T1}, and wall thickness of back tripod leg x_{T2}. The shape variables include vertical arc height of front and back tripod leg x_{q1} and x_{h1}, upper channeling depth of front and back tripod leg x_{q2} and x_{h2}, nether channeling depth of front and back tripod leg x_{q3} and x_{h3}, lateral channeling depth of front and back tripod leg x_{q4} and x_{h4}, and horizontal arc height of back tripod leg x_{h5}. By considering both the mesh quality in morphing process and actual production condition, data ranges of each variable are set as Table 2. Partial structure shape morphing is shown as Fig.4.

Table 2 Data range of tripod structure variables

Design variables	Initial value/mm	Lower limit/mm	Upper limit/mm
x_{T1}	1.2	0.8	2.0
x_{T2}	1.2	0.8	2.0
x_{q1}	0	-50	50
x_{q2}	0	0	5
x_{q3}	0	0	5
x_{q4}	0	0	5
x_{h1}	0	-50	50
x_{h2}	0	0	5
x_{h3}	0	0	5
x_{h4}	0	0	5
x_{h5}	0	-50	50



(a)Vertical morphing of front tripod leg



(b) Horizontal morphing of back tripod leg

(c)Channeling morphing of front tripod leg
Fig.4 Shape morphing of tripod legs

5 Variable screen

Plackett-Burman designs are highly fractionalized designs to screen the maximum number of main effects in the minimum number of experimental runs. PB designs are very economical, and are efficient in screening when only main effects are of interest. Variables with unapparent effects can be screened out without much loss of accuracy in further design studies such as optimization. This reduces the problem dimension which in turn will reduce the computational expenses as well as the amount of data to be investigated.

Effects are the changes in the responses produced by changes in the levels of the design variables. Main effect of a factor is the change in response produced by a change in the level of the factor alone, averaged across the levels of other factors. Effects are calculated by

$$E(x_i)=\sum(F_i^+-F_i^-)/N \tag{1}$$

where $E(x_i)$ is the effect of design variable x_i, F_i^+ and F_i^- are respectively corresponding goal function values of x_i at upper level and lower level, N is the experiment times.

Effects of each variable are shown in Table 3. From Table 3, we can see that x_{T1}, x_{T2}, x_{q1} and x_{h1} have large effects on y_1, y_2 and m.

Table 3 Effects of each variable

	y_1/(N·mm^{-1})	y_2/(N·mm^{-1})	m/Kg
x_{T1}	3958	137	0.64
x_{T2}	6121	1504	1.49
x_{q1}	3219	9	0.015
x_{q2}	-653	44	0.031
x_{q3}	-271	83	0.01
x_{q4}	-343	-139	0.054
x_{h1}	3344	435	0.004
x_{h2}	649	-160	0.076
x_{h3}	300	-43	0.033
x_{h4}	185	-43	0.058
x_{h5}	290	223	0.004

6 Approximate model

6.1 Experiment design

High-precision approximate model largely depends on sampling technique in design space. Reasonable sampling method can generate sample points with uniform distribution to guarantee the precision of approximate model. Hammersley sampling technique is adopted in this paper. It belongs to the category of quasi-Monte Carlo methods. This technique uses a quasi-random number generator, based on the Hammersley points, to uniformly sample a unit hypercube. Hammersley sampling is an efficient sampling technique which provides reliable estimates of output statistics using reasonably fewer samples. It also provides good, uniform properties on a k-dimensional hypercube. This is an advantage over Latin Hypercube sampling, providing good uniformity properties of just one dimension. To get a qualified fitting function using a DOE (Design of experiment) with Hammersley sampling, a minimum number of （N+1)(N+2)/2 runs should be evaluated(N is the number of design variables). In this paper, 40 groups of samples were generated to create 4×40 experiment design matrix as shown in Table 4 (simulation results are also listed).

Table 4 Experiment design matrix

Serial number	x_{T1}/mm	x_{T2}/mm	x_{q1}/mm	x_{h1}/mm	y_1/(N·mm^{-1})	y_2/(N·mm^{-1})	m/kg

1	0.83	1.4	-16.67	-30	27410.61	7613.38	4.14
2	0.86	1.1	16.67	-10	34300.35	7617.358	3.45
3	0.89	1.7	-38.89	10	33690.05	6740.867	4.91
4	0.92	0.95	-5.56	30	32914.8	6390.51	3.16
5	0.95	1.55	27.78	-46	29280.45	9158.721	4.62
6	0.98	1.25	-27.78	-26	27796.82	6237.043	3.93
7	1.01	1.85	5.56	-6	41985.33	10664.66	5.38
8	1.04	0.875	38.89	14	35384.19	5610.745	3.1
9	1.07	1.475	-46.3	34	31428.41	5453.913	4.56
10	1.1	1.175	-12.96	-42	27396.54	7161.533	3.87
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38	1.94	1.26875	21.6	18.8	48769.9	8715.557	4.92
39	1.97	1.86875	-33.95	38.8	43921.32	8135.233	6.38
40	2	0.89375	-0.62	-37.2	34718.29	6903.628	4.09

6.2 RBF approximate model

Radial basis functions are developed for scattered multivariate data interpolation. The method uses linear combinations of a radially symmetric function based on Euclidean distance [9]. The response functions can be approximated by using a RBF model. References [10, 11] indicate that the overall performance of RBF is superior to Kriging method and Response Surface method while building approximate model. RBF shows good property in complicated function approximation. A RBF model is expressed as

$$\tilde{g}(x) = \sum_{i=1}^{n} w_i \Phi(\|x - c_i\|) \tag{2}$$

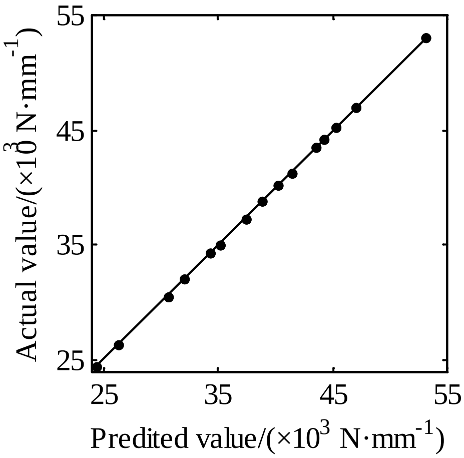
where n is the number of sampling points, w_i is unknown weighting coefficient to be determined, x is the vector of input variables, c_i is vector of input variables at the ith sampling point.

Gaussian basis function is adopted in this paper, which can be expressed as

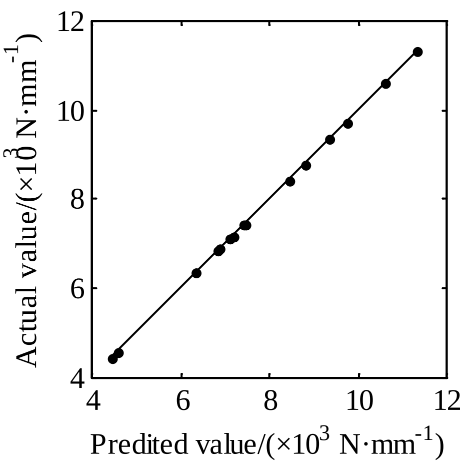
$$\Phi = \exp(-\frac{\|x - c_i\|^2}{2\delta^2}) \tag{3}$$

where δ is width of Gaussian basis function.

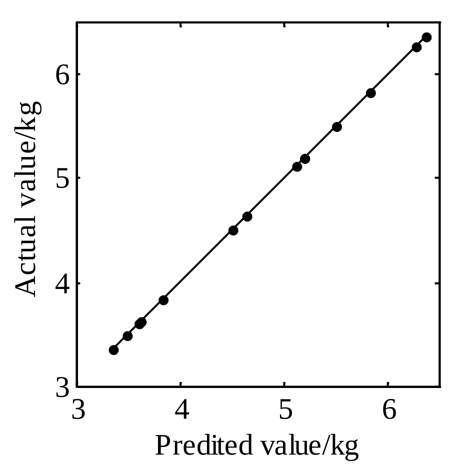
RBF approximate model was estimated with the experiment matrix samples generated by Hammersley technique. To measure the accuracy of approximate model, 15 groups random samples were generated after building approximate model, then the result calculated by finite element program is compared with approximate model for error analysis. In Fig.5, response points uniformly distribute on both sides of straight line. And the R^2 values of three responses are all close to 1, showing that approximate model's accuracy is very high and it can replace the finite element model for optimization.



(a) R_{y1}^2=0.9985



(b) R_{y2}^2=0.9847



(c) R_m^2=0.9999

Fig.5 Error analysis

7 Multi-objective optimization based on approximate model

In multi-objective optimization, optimal result is not a single solution, but a solution set called Pareto-optimal solutions, and its image in objective function space is called Pareto front.

Multi-Objective Genetic Algorithm (MOGA) takes advantage of the Genetic Algorithm (GA) to perform optimization of multiple objective functions with or without constraints. The goal of MOGA (as for all multi-objective optimization algorithms) is to produce a set of Pareto-optimal solutions instead of only one solution, the points of the Pareto front being non-dominated solutions.

For improving gun tripod's rigidity and considering lightweight requirement, multi-objective optimization mathematical model of gun tripod is expressed as

$$\begin{aligned} &\textit{minimize} \quad && y(x)=[y_1(x), y_2(x)]^{\mathrm{T}} \\ &s.t. && x \in (x_L, x_U) \\ & && m(x) \le m_0 \end{aligned} \tag{4}$$

where, $y_1(x)$, $y_2(x)$ are tripod's longitudinal stiffness, transverse stiffness respectively; x_L is the lower limit of design variable and x_U is the upper limit of design variable; $m(x)$ is the mass of tripod; m_0 is the upper limit of tripod mass which is decided by design requirement. Here, m_0 is set to be 5.0 kg.

Population size of MOGA is 300 and iteration is 50. Optimized Pareto front is shown as Fig.6. Five groups solutions of Pareto-optimal solutions are listed in Table 5.

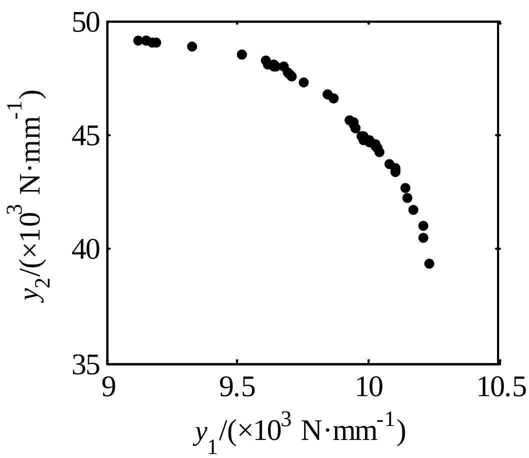


Fig.6 Pareto front

Table 5 Pareto-optimal solutions

Serial number	x_{T1}/mm	x_{T2}/mm	x_{q1}/mm	x_{h1}/mm	$y_1/(\mathrm{N \cdot mm^{-1}})$	$y_2/(\mathrm{N \cdot mm^{-1}})$	m/kg
1	1.02	1.68	10.35	12.28	43784	10076	4.993
2	1.11	1.64	9.43	17.04	44993	9971	4.990
3	1.80	1.36	17.95	22.64	49177	9115	4.999
4	0.88	1.74	-2.43	15.09	40566	10208	4.993
5	1.22	1.60	14.16	9.56	45696	9924	5.000

8 Conclusion

Mesh morphing technique is applied to the structural optimization of Gatling gun tripod. By mesh morphing technique, structure dimension and structure shape are combined as optimal variables to build parameterized finite element model. Hammersley sampling method is used in design space to get uniformly distributed sample points and high-precision RBF approximate model is derived to replace finite element model which is computationally time-consuming. With comprehensive application of mesh morphing technique, approximate model method and Multi-Objective Genetic Algorithm, dimension optimization and shape optimization are combined to perform multi-objective optimization for Gatling gun tripod. The obtained Pareto-optimal solutions can improve longitudinal stiffness and transverse stiffness of tripod, which is promising in the future application.

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