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Development of a New Model for the Fixture Design and Clamping Optimization*

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***Abstract* - Workpiece deformation must be controlled in the manufacturing process and other engineering application. Fixture configuration (position), clamping force and temperature are main aspects that influence the degree and distribution of Workpiece deformation. This paper takes large optical glass as an example, develop a new multiple kernel learning method to discuss the optimal fixture design. The proposed method uses two layers regressions to group and order the data sources by the weights of the kernels and the factors of the layers. Since that, the influences of the clamps and the temperature can be evaluated by grouping them into different layers. Then, based on the proposed model, the optimal magnitude and positions of clamping forces can be obtained. The experiments show is effective for the optical element clamping optimization analysis.**

Index Terms* - *Optimal Fixture design, integrated fixturing model, multiple kernel regression

I. INTRODUCTION

Fixture design is an important procedure in manufacturing engineering, especially in machining and assembling of Sophisticated Large-scale thin-walled workpiece. Minimizing the deformations of the workpiece is the critical principles of Fixture Layouts design and analysis. Therefor Fixture design aims to determine the appropriate the positions of locators, clamps and supports, applied clamping forces and some other environment parameters, e.g. temperature, which is the reasons cause workpiece deformations.

Traditionally, machining fixtures are designed and manufactured through trial-and-error. It relies heavily on the designer's experience to choose the positions of the fixture elements and to determine the clamping forces, which prove to be both expensive and time-consuming to the manufacturing process. In this case, there were many high-efficiency and convenient methods based on finite-element (FE) modeling approach and rigid-body modeling approach ever taken to illustrate the relation of fixture-workpiece system deformation and fixture layout and clamping force and optimize the fixture layouts to obtain the positions and clamping force.

Lee and Haynes [1] were amongst the first to use FEM for the fixture design and synthesis. Kashyap et al. [2] using the finite element modeling choose the appropriate position of clamping and supporting points, to ensure the workpiece has a minimum deformation in the normal direction of the main location surface. B. Denkena et al. [3] reported the extensive works based on the finite element approach. King and Hutter [4] presented a method for optimal fixture layout design using a rigid body model of the workpiece system.

In order to optimize the fixture layout properly, there are many fixture layout optimization methods/algorithms have been carried out on fixture design. Menassa et al. [5] first applied optimization using nonlinear method to fixture design. Cho [6] conducted parametric modeling iterations to optimize the design of the elliptical tertiary mirror fixture system. There are some evolutionary methods/algorithms was a useful technique in solving the optimization problems. Li and Shiu [7] determined the optimal fixture configuration design for sheet metal assembly using GA. Chen et al. Prabhaharan et al. [8] used an ant colony system as an optimization tool for minimizing the critical dimension deviation and allocating the cost-based optimal tolerances. Dong and Su[9]proposed a self-adaptive population dimension Differential Evolution (DE) method is proposed to optimize the fixture design for large optical glass assembly.

In some situations, the environment parameters (temperature, Humidity, gravity, etc.) have to be considered in the Optimization of Fixture Layouts design, e.g. Large-scale glass laser system apply to the high power laser field. Yu et al. [10] analyzed the thermal behaviors of three different support systems, which they called by multi-pints support, four edge support and side face support, for fused silica optics with the finite element method, so that a suitable support schemes to reduce the residual stress was designed based on the analysis. Cho et al. [11] conducted the FEA and optical analyses for the support frame design. They analyzed the static deformation of gravity and thermal, and then established a fixturing matrix to compensate potential errors using an active optics system. However, in the previous integration model, the thermal and structural analyses are conducted independently. And, it is difficult to obtain a near global optimal set of clamps.

In allusion to the problems mentioned above, this paper aims to construct approximations for an unknown integrated fixturing function, which is better to describe the relation of fixture-workpiece system deformation and the mechanism properties and the thermal properties of the fixture. Support vector machine (SVM) has been introduced as a powerful method for classification and regression problems (called Support Vector Regression (SVR) [12]). The approximation of

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a function using SVM has some attractive properties [13]. For example, it does not suffer from the overfitting problem and it has good generalization ability. These features suggest that SVR may be a good candidate for constructing approximations for unknown nonlinear functions in the area of mechatronics, such as dynamics identification, friction modeling, and electromyography classification, e.g., references [14-15],.

In this paper, the optimal fixture design for the large plates of optical glass is discussed. A new multiple kernels learning method is developed to build the nonlinear coupling between the clamping force, the thermal and the deformation of the optic. Then, based on the proposed model, the optimal magnitude and positions of clamping forces can be obtained.

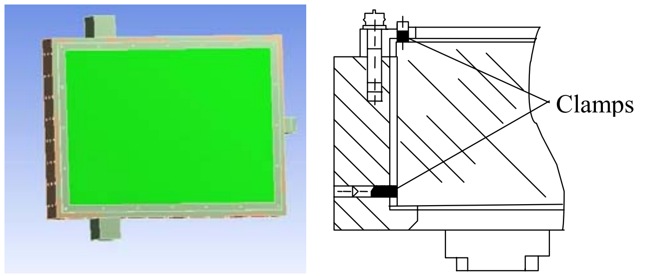
The rest of the paper is arranged as follows: Section II introduces some statements related to this work. Section Ⅲ describes the canonical SVM methods. Section Ⅳ presents a multiple kernels regression method to construct the integrated fixturing model, which is able to describe the nonlinear coupling between the clamping force, temperature and the deformations of the optic. In Section V, experiments and simulation are given to illustrate the efficiency of proposed method.

II. PROBLEM STATEMENT

A fixture (support structural) of the large scale optics in high power laser system is generally composed of two types of elements: a carriage, some clamps for firmly holding the optic during laser running. The design methodology of the support frame of the fixture in high power laser is similar to the design of the fixture in sheet metal manufacturing, where we all try to find a set of clamps, and select the suitable clamping forces to minimize the target deformation.

As we know, the optical properties are extremely sensitive to the thermal and residual stress, so, excellent exposure need to be applied to reduce the stress in the laser running. Comparison with the fixture design in traditionally manufacturing industry (the review of the research on optimal fixture design in manufacturing can be found in reference [16]), the major design constraints of the support structure in high power laser system is that the surface shape error induced by thermal residual stress in laser running is critical for the placements of the clamps. That is, the fixturing model needs to describe the relationship between the placements of the clamps, the clamping forces and the temperature.

In order to totally restrain the optic on the narrow side surface, and make the optical glass force uniformly with low stress clamping, plastic gel nails are usually used to attribute the interfacial friction between the support frame and optic. Figure 1 shows the mechanical structure of the support frame. As shown in Figure 1 (a), the support carriage is comprised of a precisely machined frame with threaded holes and a set of plastic gel nails. In Figure 1 (b), the clamps are at the carriage of the frame, which would apply clamping force to the optic.



(a) (b)

Fig.1 Structure of support system

The design of support carriage is the layout of the clamps on the threaded holes and the actuating force of applied on the optic, which ensure the optic is firmly hold by the frame with minimal shape deformation under different working temperature. The nonlinear fixturing model is critical for the optimal design of the support frame.

In this paper, we will present a novel support vector regression method for the construction of the nonlinear fixturing model. In the following, some concepts about support vector will be firstly presented.

Ⅲ. SUPPORT VECTOR REGRESSION

A. *Standard Support Vector Regression*

Suppose there is a set of training data $\{(x_i, y_i)\}_{i=1}^{n} \subset {}^{D} \times$, where ¡ ^{D} denotes the space of the input patterns, each x_i denotes the input space of the sample and has a corresponding target value y_i for $i = 1,\ldots,n$. The kernel SVR*'s* basic idea is to find a nonlinear regression function $f: {}^{D} \rightarrow$ of the kind[16]

$$f(x) = \langle \omega, \phi(x) \rangle + b \tag{1}$$

Where $\phi(x)$ maps a data point x into a higher dimensional feature space, ω is the weight coefficients, b is the threshold.

The parameters can be trained by solving the following quadratic optimization problem [20].

$$\begin{aligned}
&\min_{\mathbf{w},b,\xi,\xi^*} \ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\mathbf{1}^T(\xi + \xi^*) \\
&\qquad \text{w.r.t. } \omega,\ \xi,\ \xi^*,\ b \\
&s.t. \quad \mathbf{y} - \left(\langle \mathbf{w}, \Phi(\mathbf{x}) \rangle + b\right) \le \mathbf{1}\varepsilon + \xi \\
&\qquad \left(\langle \mathbf{w}, \Phi(\mathbf{x}) \rangle + b\right) - \mathbf{y} \le \mathbf{1}\varepsilon + \xi^* \\
&\qquad \xi, \xi^* \ge 0
\end{aligned}$$

where ω is the vector of weight coefficients, C is a predefined positive trade-off parameter between model simplicity and classification error, ε is ε -tube of the epsilon insensitive Loss Function[SVR], ξ , ξ^* is the two vector of slack variables for each data point and b is the bias term.

Solving the equation, the regression function (1) can be rewritten as

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)k(\mathbf{x},\mathbf{x}_i)+b \tag{2}$$

Where $k(x_i,x_j)=\left\langle \phi(x_i),\phi(x_j)\right\rangle$ is the kernel function and α_i,α_i^* is the vector of dual variables corresponding to each separation constraint.

*Multiple Kernel Support Vector Regression (**MKSVR**)*

In recent years, **MKSVR** method has been proposed [17-19], where we use multiple kernels instead of selecting one special kernel function and its corresponding parameters. The combination of basic kernels shows two benefits [17]: (a) Using a specific kernel may be a source of bias, and in allowing a learner to choose among a set of kernels, a better solution can be found. (b) Different kernels may be using inputs coming from different representations possibly from different sources or modalities. For detailed and comprehensive review works on **MKSVR,** see reference [18]; here, we simply review the fundamental ideas and define our notation.

In canonical **MKSVR**, the functional forms are described by [19]

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K_M(x,x_i^m)+b \tag{3}$$

And, K_M is chosen to be a set of convex combination of M predefined base kernels

$$K_M(x,x_i^m)=\sum_{m=1}^{M}\mu_m k_m(x,x_i^m) \tag{4}$$

where μ_m denotes the weight of the m^{th} base kernel.

Therefore, the functional form of the regression function (3) becomes

$$f(x)=\sum_{i=1}^{N}\left(\alpha_i\sum_{m=1}^{M}\mu_m k_m(x^m,x_i^m)\right)+b \tag{5}$$

where $f(x)$ is expressed as a linear combination of the kernel function $k_m(x^m,x_i^m)$ relative to the data point x_i^m in the feature space ¡^{D_m} , and the type and the number m of kernels $k_m(x^m,x_i^m)$ used in the linear combination have to be chosen a priori.

As we know, in most mechanical applications, the role of difference sources can be known in previous. In such a case, the hierarchical method is a possible way to represent the relative importance of the information sources. The hierarchical method is that the importance of the sources are grouped and ordered in different layer depends on the role of the sources. In the practical, we know that the temperature play a more important role for the influence function than the set of the support layout and the set of the clamping forces.

In the following, a hierarchical method, we called Multiple Kernel Support Vector Functional Regression (MKSVFR), is developed to construct the fixturing model.

Ⅳ. MULTIPLE KERNEL SUPPORT VECTOR FUNCTIONAL REGRESSION

In this section, we will present the new regression method for the construction of the integrated fixturing model for the design of the support frame.

A. The structure of MKSVFR

Without loss of generality, Suppose there is a set of training data $\{(x^i,y^i)\}_{i=1}^{n}\subset {}^{D}\times$, where $x^i=(\{(S_k^i,C_k^i)\}_{k=1}^{m},T^i)$, $y^i=\{(y^i)\}_{k=1}^{m}$. S_k^i is the position of the clamps and C_k^i defines the clamping forces under the temperature T^i . We define the MKSVFR model as follows, which is composed of two layers:

(a) In the first layer, a sub regression functions f^i , which represents the relationship between the output y_k^i with respect to the input vector ((S_k^i,C_k^i));

(b) In the second layer, a total regression function f *describes* the relationship between the sub functions f^i with respect to the input t^i . It should be noted that in the higher layer, the regression represent the relationship of a function and a set of input data, i.e., the relationship of f^i and the sample data T^i .

The mapping from a function to the input data is different with the mapping of two vectors. Since that, we use a new notation, functional regression, to represent the model.

The output of the MKSVFR model is obtained by the mapping as following

$$f(x)=F\left(f^1(x^1),\mathrm{K}\ ,f^n(x^n)\right) \tag{6}$$

where $f^j(x^j)$ is j^{th} sub-regression function in the first layer, and $x^i=(\{(S_k^i,C_k^i)\}_{k=1}^{m},T^i)$ denotes the input vector, F is usually a nonlinear mapping.

B. The sub regression function in the first layer

In this paper, we assume all the sub-regression functions have a same functional from, which based on the MKSVR. Thus, the i^{th} sub-regression function is

$$f^i(x^i)=\sum_{m^i=1}^{M^i}\mu_{m^i}^i\left\langle \omega_{m^i}^i,\Phi_{m^i}^i(x^i)\right\rangle+b^i \tag{7}$$

Similar to the parameter learning in localized multiple kernels learning [18], we adopt a two-stage alternant optimization approach to find the regression parameters. When we fix the weight $\mu_{m^j}^j$, the problem becomes convex and we obtain the following dual problem

$$\max J$$

$$J=-\frac{1}{2}\sum_{k=1}^{N}\sum_{i=1}^{N}a_k^i a_k^i\left(\sum_{m^i=1}^{M^i}\mu_{m^i}^i k_{m^i}^i(x_i^{i,m^i},x_i^{i,m^i})\right)-\sum_{k=1}^{N}y_k^i(\alpha_k^i-\alpha_k^{*i})-\varepsilon\sum_{i=1}^{N}(\alpha_k^i+\alpha_k^{*i})$$

$$\text{s.t.}\quad \sum_{k=1}^{N}(\alpha_k^i-\alpha_k^{*i})=0$$

$$C \geq \alpha_k^i \geq 0 \qquad \forall k$$
$$C \geq \alpha_k^{*i} \geq 0 \qquad \forall k$$

And, the weight function $\mu_{m^j}^j$ is defined as

$$\mu_{m^i}^i = \frac{\exp\left(\left\langle \mathbf{\upsilon}_m^i, \mathbf{x}^i \right\rangle, \upsilon_{p0}^i\right)}{\sum_{j=1}^{M^i} \exp\left(\left\langle \mathbf{\upsilon}_j^i, \mathbf{x}^i \right\rangle, \upsilon_{j0}^i\right)} \tag{8}$$

where υ_m^i and υ_{m0}^i are the parameters of the gating model function and the softmax guarantees nonnegativity.The gating model parameters are updated at each iteration by calculating $\partial J(\mu_{m^i}^i)/\partial \upsilon_{m0}^i$ and $\partial J(\mu_{m^i}^i)/\partial \upsilon_m^i$, and then performing a gradient-descent step.

After determining the finial $\mu_{m^i}^i$ and *SVM* solution, we can obtain the resulting discriminant function $f^i(x^i)$ in the lower layer.

C. Functional regression in the second layer

In the lower layer, we build the relationship between the input vector (S_k^i, C_k^i) and the output y_k^i to get the sub regression function $f^i(x^i)$. In the top layer, the input vectors become $\{f^i(x^i), T^i\}$, hence, we establish a new regression relates to the input data $\{f^i(x^i), T^i\}$

Suppose that the total function is descried by

$$F(x,t) = F\left(f^j(x^j), t_j\right)$$

According to the kNN regression [20] simply assigns the weight for the regression function to be the average of the values of its k nearest neighbors, in which the nearer neighbors contribute more to the average than the more distant ones, We define the top regression functional form as

$$F(X) = \sum_{i=1}^{n} \varpi_i(T^i) f^i(x^i) + \theta(x^i) \tag{9}$$

Where $\varpi_i(T^i)$ indexes the weight of the i^{th} sub-regression function, and $\theta(x)$ is a bias term under the condition of x . In order to calculate the weight $\varpi_i(T^i)$, according the canonical K Nearest Neighbors – Regression, we introduce the Gaussian kernel to establish the relationship between the distance of Nearest Neighbors and the weight $\varpi_i(T^i)$ of the i^{th} sub-regression function.

$$\varpi_i = g(\left\|T - T^i\right\|^2) \tag{10}$$

$$g = \kappa * \exp\left(\frac{\left\|T - T^i\right\|^2}{\sigma^2}\right) + \lambda$$

$$\sum_{i=1}^{n} \varpi_i = 0$$

In conclusion, the computation of the top-regression function is summarized in Algorithm 3.

Algorithm 1: MKSVFR-top regression function

Input: the temperature T^i , he clamps and the clamping forces (S^i, C^i) and the sub-regression $f^i(x^i)$.

Output: the top-regression.

1. **For** each (S^i, C^i) learned before **do**
2. Calculate the value of the sub-regression $f^i(x_i^i)$ with the clamps and the clamping forces (S^i, C^i)
3. Calculate the distance of Nearest Neighbors
4. Calculate the weight $\varpi_i(X)$ of the jth sub-regression function as Eqn.(10)
5. Choose the best performing $\kappa(x_i)$ and $\lambda(x_i)$ by cross-validation procedure.
6. **End for**
7. Solve canonical SVR and get the $\kappa(X)$ and $\lambda(X)$
8. Get the the weight $\varpi_i(X)$ of the jth sub-regression function as Eqn.(11)
9. Obtain the top regression functional as Eqn.(9)

V .EXPERIMENTS AND DISCUSSION

In this section, we perform several experiments to discuss the influence of the input data. We firstly describe the creation of the input datasets. And then, we compare the proposed method and the canonical MKSVR, SVR and MKSVFR method. Finally, obtain the optimal magnitude and positions of clamping forces based on the fixturing function.

A. Datasets

The optic used in the experiment is shown in Figure 2, of which size is 430mm×430mm×20mm. As the optic is vertically mounted on the support frame, its optical axis is perpendicular to the support plane.

The basic data of the structural materials, i.e., the clamps and the frame, and the optic material are given as Table I.

TABLE I
OPTIC AND SUPPORT ELEMENT PROPERTIES

Variable	optic	plastic nails	frame
Young's Modulus	7.92GPa	0.023GPa	206GPa
Poisson's ratio	0.25	0.46	0.28
Density	2530kg/m^3	1100kg/m^3	7850kg/m^3

The data sets created by the ANSYS software are explained as Fig.2.

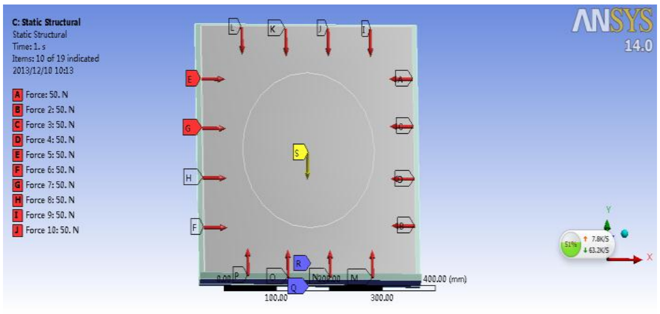


Fig.2 ANSYS software environment to created datasets

There are 4 clamps on each side of the support frame, and all the 16 clamps can apply the clamping force on the optic. Under different temperature, even the same clamping force will cause various shape deformation. According the practical and to specialize the data space promote the regression accuracy, there some constrains about the input the position of the clamps and the clamping forces when we created datasets. The constrains as follow

Symmetry constrain: to reduce the shape deformation which is the caused by the asymmetry, we propose position of the clamps are the clamping forces applied on the left and right sides of the optic are symmetry.

Force structures constrain: to reduce the shape distortion, we propose the difference between the clamping forces of two adjacent sides must not exceed 20N.

Table II shows several groups of date sources (the total number of the training data is nearly 1800), in which T. denotes the temperature. Pos. denotes the position of the clamps. F. denotes the clamping force. Deform. represents the deform of the optics.

TABLE II
THE INPUT VECTOR AND THE OUTPUT

T.	Pos.	Force	Deform.
22	(40,40,40.40; 40,0,0,40; 40,0,0,40;40,40,40.40;)	(40,40,40,40)	1.2294
22	(40,40,40.40; 40,0,0,40; 40,0,0,40;40,40,40.40;)	(20,30,30,40)	1.3402
25	(40,40,40.40; 40,0,0,40; 40,0,0,40;40,40,40.40;)	(20,30,30,40)	2.5915
25	(40,40,40.40; 40,0,0,40; 40,0,0,40;40,40,40.40;)	(20,30,30,40)	2.2915
…	…	…	…
28	0,70,70.0; 0,70,70,0; 0,70,70,0;0,70,70.0;)	(70,70,70,70)	1.6131

B. Numerical Results

We implement the algorithm in MATLAB. For SVR, MKSVR and MKSVFR, we take the tube width, ε, as 0.01 and the regularization parameter, C, as 100000. We then choose the best performing σ by cross-validation procedure.

For all performed experiments; we quantified the prediction performance with mean absolute percentage error (MAPE). They can be defined as

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|X_{Ai} - X_{Fi}|}{X_{Ai}} \times 100$$

The performance of the MKSVFR-FR and MKSVFR-PR are compared with SVR, MKSVR and L-MKSVR models based on the data sources given in Table II. This comparison is depicted in Figure 3 and shown in Table III.

TABLE III
COMPARISON OF THE MMKSVR AND OTHER

MODEL	MAPE(%)
MKSVFR	5.80
MKSVR	6.32
SVR	9.46

It can be seen from Figure 3, the root mean square errors and the mean absolute percentage error are reducing with the number of training data increasing. And the MAPE(%) less than 10%, it can illustrate the MKSVFR model we proposed is effective and feasible. Meanwhile, we can also know that, the absolute percentage errors shown in Figure3 of the proposed MKSVFR method are much better than the results of MKSVR and SVR.

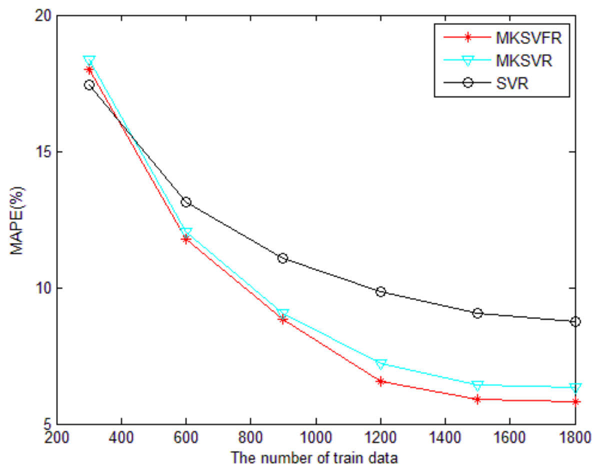


Fig.3 The mean absolute percentage errors

C. The optimal design of the support frame based on the integrated fixturing model

Once the fixturing model is constructed as described in Subsection-B, we are able to detect the optimal clamp placements and the clamping force under different temperature. The fixturing function based on MKSVFR method is given by Equation (9)

$$F(X) = \sum_{i=1}^{n}\varpi_i(T^i)f^i(x^i) + \theta(x^i)$$

In general, we can compute the optimal value of $F(X)$, and then can select an set of clamps related to the minimum value. That is, it is able to get the optimal design of the support frame, which is possible to obtain the minimum shape deformation of the optic.

We perform several experiments to show the deformations of the optic related to the temperature, the clamp placements and the clamping forces. Denoted the minimal deformation of the optic by

$$D_{\min} = \min(\max F(X))$$

Thus, we can compute the clamp placements, the clamping force and the temperature, which corresponds to the global minimal deformation of the optic. The minimal deformation of the optics can then be obtained via the fixturing model constructed r by MKSVFR method. The results are listed in Table IV

TABLE IV
THE MINIMAL DEFORMATION AND THE RELATED CLAMPING FORCES

	T	Pos.	F.(N)	Deform
MKSVFR	21.73	(0,15,15.0 0,20,20,0; 0,20,20,0; 30,30,30.30;)	(15,20, 62,60)	0.70756

The simulation result of deformation of the optic in ANASYS is shown in Figure 4, in which the max deformation of the optic is 0.7251. That is, the error of the fixturing model is 2.4789%

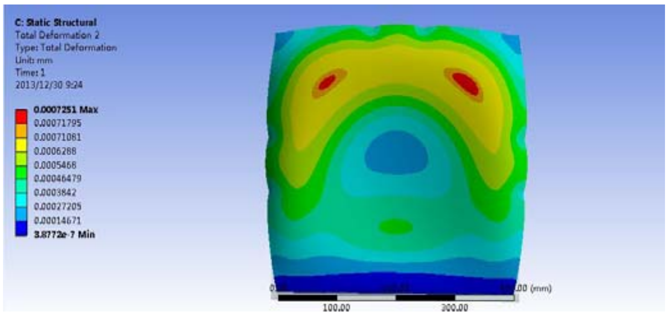


Fig.4 The deformation of the optic

VI. CONCLUSION

In this paper, we have proposed a new approach that can be used to solve the optimal design of the support frame of the optical system. The approach uses two layers regression to construct the fixturing model of the frame, of which first layer is to obtain a set of sub-regression functions f^i. And then, the second layer establishes a top-regression function f, in which the set of sub function f^i are taken as input data. We compute the top regression function by kNN method.

Based on the fixturing model of the frame we can compute the minimal deformation of the optic and the related clamp placement and the environmental temperature. We then can get an optimal design of the support frame and adjust the environmental temperature by the temperature control system. Since that, thousands of large optics mounted on the support frame is able to produce the high energy.

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