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A Minimax Fitting Algorithm for Ultra-Precision Aspheric Surfaces

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Abstract

Aspheric lenses show significant superiority over traditional spherical ones. The peak-to-valley form deviation is an important criterion for surface qualities of optical lenses. The peak-to-valley errors obtained using traditional methods are usually greater than the actual values, as a consequence causing unnecessary rejections.

In this paper the form errors of aspheric surfaces are evaluated in the sense of minimum zone, i.e. to directly minimize the peak-to-valley deviation from the data points to the nominal surface. A powerful heuristic optimization algorithm, called *differential evolution* (DE) is adopted. The control parameters are obtained by meta-optimization. Normally the number of data points is very large, which makes the optimization program unacceptably slow. To improve the efficiency, alpha shapes are employed to decrease the number of data points involved in the DE optimization.

Finally numerical examples are presented to validate this minimum zone evaluation method and compare its results with other algorithms.

Keywords: aspheric surface, peak-to-valley deviation, differential evolution, alpha shape
2000 MSC: 90C47, 90C31, 65K10

1. Introduction

Aspheric lenses show notable superiority over conventional spherical lenses in that a multiple-element spherical lens can be replaced by a single aspheric lens. Aspheric surfaces can be represented with [1],

$$z = \frac{r^2/R}{1 + [1 - (1 + k)r^2/R^2]^{1/2}} + A_4r^4 + A_6r^6 + \dots \quad (1)$$

with $r = (x^2 + y^2)^{1/2}$.

Here R is the radius of curvature of the underlying sphere, k is the conic constant and $\{A_i\}$ are the magnitudes of higher order deviations from sphericity.

The form error of a manufactured lens plays an essential role in its performances. Currently the PV, peak-to-valley deviation, is still a very commonly adopted specification for surface quality [2], despite its recognized drawbacks for characterizing surfaces and lack of link to optical performances. Most current commercial software applies the least squares method to fit the nominal surface from data and calculates the PV error from the difference between the maximum and minimum residuals. However this approach is likely to overestimate the form tolerance and lead to unnecessary rejections.

Here we attempt to directly minimum the peak-to-valley deviation,

$$\min(\max_i d_i - \min_i d_i) \quad (2)$$

where $d_i = \pm\|\mathbf{q}_i - (\mathbf{R}\mathbf{p}_i + \mathbf{t})\|$ is the signed distance from an arbitrary measured point \mathbf{p}_i to its projection \mathbf{q}_i onto the nominal surface. \mathbf{R} is the optimal rotation matrix and \mathbf{t} is the translation vector.

This minimax problem is not continuously differentiable, thus very difficult to be solved. This paper presents a heuristic optimization algorithm, called *differential evolution* (DE), to conduct minimum zone evaluation of aspheric surfaces. This method shows great superiorities on stability and accuracy, and makes a good balance between exploration and exploitation.

2. A differential evolution algorithm

At each generation, a Donor vector \mathbf{v}_i is generated for each individual of the population (called *genome* or *chromosome*) $\{\mathbf{y}_i | i = 1, \dots, NP\}$. It is the method of creating this Donor vector that demarcates between the various DE schemes. Two mutation schemes ‘DE/rand/1/bin’ and ‘DE/current to best/2/bin’ are applied [3, 4],

$$\mathbf{v}_i = \begin{cases} \mathbf{y}_r + F(\mathbf{y}_s - \mathbf{y}_t), & \text{rand}[0, 1] < p \\ \mathbf{y}_i + F(\mathbf{p}_g - \mathbf{y}_i + \mathbf{y}_r - \mathbf{y}_s), & \text{otherwise} \end{cases} \quad (3)$$

where r, s and t are integers randomly selected from the range $[1, NP]$ (excluding i). $F \in [0, 2]$ is used to scale the differential vector, $p \in [0, 1]$ is a user-set parameter and $\text{rand}[0, 1]$ is a random number uniformly generated in the interval $[0, 1]$.

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These two strategies are used very commonly in literature and perform well on problems with distinct characteristics. ‘DE/rand/1/bin’ demonstrates good diversity while ‘DE/current to best/2/bin’ shows good convergence property.

After the mutation phase, a ‘binomial’ crossover operation is applied,

$$u_{ij} = \begin{cases} v_{ij} & \text{if } \text{rand}_j[0, 1] \leq CR \text{ or } j = j_{rand} \\ y_{ij} & \text{otherwise} \end{cases} \quad (4)$$

where $CR \in [0, 1)$ is a user specified crossover constant and j_{rand} is a randomly chosen integer in $[1, NP]$ to ensure that the trial vector \mathbf{u}_i will differ from \mathbf{y}_i by at least one component. The subscript j refers to the j -th dimension.

Then a selection operation follows,

$$\mathbf{y}_i^{k+1} = \begin{cases} \mathbf{u}_i^k & \text{if } f(\mathbf{u}_i^k) < f(\mathbf{y}_i^k) \\ \mathbf{y}_i^k & \text{otherwise} \end{cases} \quad (5)$$

with k and $k + 1$ denoting the individuals in the k -th and $(k + 1)$ -th generations respectively and f representing the objective function to be minimized.

The pseudocode for optimization program is shown in Algorithm 1.

```

Input:  $NP, CR, F, \mathbf{X}, \mathbf{y}_0$ 
//  $\mathbf{X}$ : data points,  $\mathbf{y}_0$ : rough guess of
   solution
Initialize population  $\mathbf{Y}$ ;
 $k = 0$ ; // generation number
while  $k < k^{max}$  do
     $k++$ ;
    for  $i = 1$  to  $NP$  do
        Evaluate fitness  $f(\mathbf{y}_i)$ ;
        Update global optimum  $\mathbf{p}_g$ ;
        Mutation of  $\mathbf{y}_i$  using Eq (3);
        Crossover and selection of  $\mathbf{y}_i$  using Eqs
        (4),(5);
    end
    if termination condition satisfied then
        Break;
    end
end
Output:  $\mathbf{p}_g$ 
Algorithm 1: A differential evolution algorithm

```

The optimal configuration, i.e. the values of the population size NP , the scaling factor F and the crossover rate CR , is very problem-dependent. According to the ‘No-free-lunch theorems’, it is not possible to make the optimization program widely applicable whilst maintaining the best performance at every situation[5]. To obtain relatively good performance in different cases, the optimal parameter configuration is particularly obtained for each situation. Here meta-optimization is performed off-line using the Local Unimodal Sampling [6]. The running speed of this algorithm is determined by the number of fitness

evaluations. Here this number is set no greater than 20 000. The unknown variables are the five motion parameters (Rotation about x and y axes and translation along x , y and z directions), the radius R , the conic constant k and polynomial coefficients $\{A_i\}$ (if applicable). When the shape parameters are all given, and only the optimization position of the measured data is to be calculated, this becomes the localization problem, and the dimension will be 5. The recommended parameter settings for different dimensions are listed in Table 1,

Table 1: Parameter settings of DE to aspherics

D	NP	CR	F
5	23	0.866	0.7549
7	29	0.8745	0.7470
8	33	0.8884	0.7347
9	41	0.9046	0.7223
10	45	0.9148	0.7153
11	49	0.925	0.7087
12	52	0.9331	0.6972
13	55	0.9412	0.6808
14	57	0.9542	0.672
15	59	0.9636	0.6631
16	61	0.9729	0.6556

To prevent a too fast decrease of population diversity, the parameters need to satisfy the condition $2F^2 - 2/NP + CR/NP \geq 0$ [7]. Evidently it holds true for all the parameters given here.

3. Improving the computational efficiency

This optimization problem is highly nonlinear and lots of local minima exist. To get better results from the DE optimization, the space of the unknown variables is narrowed by supplying a good initial guess for the solution. The orthogonal least squares[8] method is used for this purpose.

3.1. Calculating the orthogonal distances

It is straightforward to write the function of an aspheric surface as $g(\mathbf{x}) = 0$ with \mathbf{x} being a point on the surface. Normally the projection point \mathbf{q} associated with the point \mathbf{p} is obtained from

$$\begin{cases} g(\mathbf{q}) = 0 \\ \nabla g(\mathbf{q}) \times (\mathbf{p} - \mathbf{q}) = 0 \end{cases} \quad (6)$$

using the Gauss-Newton or Levenberg-Marquardt algorithm.

But this method is time consuming, especially when there are many data points. Consequently at the first tens of iterations of the optimization program, the distance is approximated with [9]

$$d = \pm \|\mathbf{p} - \mathbf{q}\| \approx \frac{g(\mathbf{p})}{\|\nabla g(\mathbf{p})\|} \quad (7)$$

As the motion and shape parameters have been approximately identified using linear least squares, the distance d will not be very large, i.e. \mathbf{p} is reasonably near to the associated surface. Thus this approximation is acceptable. At the final iterations, the orthogonal distance is in turn calculated from Equation (6).

3.2. Reducing the number of data points

In practice, the number of measured data points may be up to millions, but actually only dozens of points determine the width of the error band (the point number is related with the number of unknown variables). If removing some 'unnecessary' points from the data set, the optimization process can be greatly accelerated. Fortunately, the alpha-shape technique meets this requirement.

An α -shape is a well-defined polytope, derived from the Delaunay triangulation of the point set, with a parameter $\alpha \in \mathbb{R}$ controlling the desired level of detail [10]. In order to improve the discrepancy, we replace the z coordinates of the data points by the signed residuals resulted from the least squares fitting and then scale the points into a unit cubic. If implementing the 3D Delaunay triangulation, i.e. organizing the discrete points into a set of tetrahedra, the real 'key points' are likely located at some tetrahedra with large circumscribed spheres, thus some tetrahedra with small circumscribed spheres can be omitted. But many 'boundary points' will be retained unnecessarily, hence the boundary and interior points are handled separately. Viewing from the z direction, the boundary points are recognized using the modified Graham scan method [11]. In the programme, the tetrahedra are sorted by their radii of circumscribed spheres (in descending order). The set for the points to be kept is initialized as null, and then the vertices of each tetrahedron are checked successively. The checking procedure is presented in Algorithm 2

Figure 1 shows a 2D example. Given 300 points, 30 points on the envelop are sampled using the α -shape technique. The number of points to be retained is directly

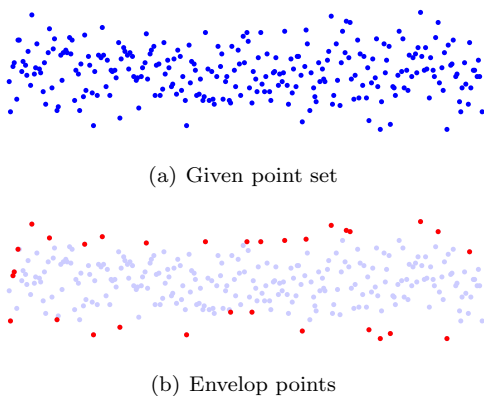


Figure 1: Point reduction using α -shapes

related with the number of unknown variables. For example, in the evaluation of flatness (resp. sphericity), there

Input: point set $\{\mathbf{x}_i\}_{i=1}^N$, points to be retained $\mathbf{Y} = \emptyset$, Delaunay tetrahedra $\mathbf{T} \in \mathbb{N}^{M \times 4}$;
 Find the boundary points \mathbf{B} ;
for $j = 1$ *to* M **do**
 for $i = 1$ *to* 4 **do**
 if $T_{ji} \in \mathbf{B}$ **then**
 if T_{ji} has the greatest positive z coordinate or the smallest negative z coordinate among the four vertices of \mathbf{T}_j **then**
 | Put T_{ji} into \mathbf{Y} ;
 end
 else
 | Put T_{ji} into \mathbf{Y} ;
 end
end
if The number of points in \mathbf{Y} satisfies the pre-set limit **then**
 | **Break**;
end
end
Output: \mathbf{Y} ;

Algorithm 2: The checking process for the vertices to be retained

are three (resp. four) variables and four (resp. five) extreme points are needed to calculate the minimum zone error. For the same reason, if n polynomial terms are involved in the aspheric function, at least $n + 8$ points are needed. To avoid removing extreme points by mistake, $2n + 14$ points will be kept in the DE optimization.

4. Experimental validation and discussion

The validity of the proposed algorithm is verified with a data set of 8100 points, as shown in Figure 2. The unit of length here is mm if not specified otherwise. The nominal shape parameters are given as $R = 520$, $k = -0.7$, $A_4 = 5.2e - 5$, $A_6 = -6.5e - 6$, $A_8 = 3.11e - 8$, $A_{10} = 3.222e - 9$. Noise with its amplitude of $\sigma = 0.98 \mu m$ is introduced with the fractal Brownian function[12]. The dimensionality of the optimization problem is 11 and the control parameters in the DE program is adopted as $NP = 49$, $CR = 0.929$ and $F = 0.74$, in accordance with Table 1.

The Differential Evolution optimization program is coded in MATLAB R2009a and run on a PC with Intel(R) Core (TM) 2 Duo CPU8500 3.16GHz, 3.24GB RAM. The program was run 100 times and the obtained best and worst PV errors and running time (including ODF least squares initial fitting and α -shape point reduction) are listed in Table 2. For comparison, the direct DE optimization without point reduction was also run 100 times and the corresponding results are also presented. From the table it can be seen that the proposed DE optimization can obtain a much smaller PV form error compared with the least squares ODF fitting, meanwhile, at a cost

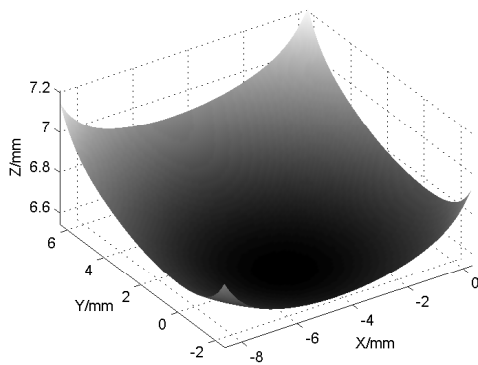


Figure 2: An aspheric surface

Table 2: Fitted results of the aspheric surface

method	ODF	DE with α		DE without α	
		max	min	max	min
PV/ μm	3.79	3.29	3.21	3.31	3.21
time/s	0.15	5.10	4.34	115.02	126.85

of much longer running time. But the average time for the whole fitting process is less than five seconds, which is acceptable in practical applications. The point reduction technique using α -shapes reduced the running by 96%. It is worth noting that obtained PV form error has not been influenced by the α -shape point reduction, which is an essential requirement to that manipulation.

5. Conclusions

This paper proposes an optimization method using differential evolution to evaluate the peak-to-valley form errors of aspheric surfaces. To make the optimization program specifically works well for different dimensions of unknown variables, the parameter configuration is obtained using meta-optimization. Additionally, the alpha shapes is adopted to get the 'envelop points' which potentially determine the PV form error, so that the points involved in the optimization program are reduced. Experimental results prove the running time can be reduced by 96% without influencing the optimization results. This program can be utilized in aspheric surface fitting to calculate the shape parameters from the given measured data points or surface matching to determine the optimal relative position between the measured data and the nominal surface.

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