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TITLE: AN ATTEMPT TO DEVELOP AN "INTELLIGENT" LENS
DESIGN PROGRAM

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An attempt to develop an "intelligent" lens design program

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Abstract

We are developing a Lens Design Program intended to operate without user intervention, and to improve its performance with repeated usage. The methodology and current status will be discussed in this paper.

Introduction

We call a technical program "intelligent" if it performs autonomously a task that ordinarily requires skilled human mental activity and simulates learning by exhibiting self-improvement in its rate of successful task performance with usage. We chose optical imaging systems as our initial attempt to develop an intelligent design program because their performance and cost can be calculated accurately without experimental verification. Although powerful computer design tools are available for that purpose, the total design activity still requires human participation.

Our approach relies on two principal elements. First, we employ a particular mathematical structure to codify the problem. Second, we use probabilistic processes where useful and appropriate.

The mathematical formulation is based on the mapping from a "configuration" space to a "performance" space. This mapping represents lens system evaluation and its inverse represents lens system design. The mapping is defined by means of a universal merit function that induces a natural and intelligently exploitable topology on the two spaces.

A promising probabilistic optimization process currently under study is a generalized simulated annealing method. In principle, this method can find, without user intervention, the global minimum of a merit function which may have many local minima.

This methodology and current status is presented in some detail in the following three sections. An outline of future work concludes the presentation.

Mathematical structure for an "intelligent" lens design program

The mathematical structure we employ to codify the lens design problem is based on a mapping between a configuration space and a performance space. These notions will now be explained briefly.

Any convenient set of variables that defines the geometry and optical properties of an optical system under consideration uniquely and self-consistently can be used to form a suitable configuration space. For example, a lens in the class of systems consisting of at most N axisymmetric spherical interfaces, with material of uniform refractive index and dispersion in the region between each pair of interfaces, requires specification of the curvature and distance from the image plane of each of the N interfaces, and the refractive indices and dispersion of the N regions between the image plane and the most distant interface, making a total of $4N$ configuration variables. In this case the configuration space has $4N$ dimensions, with each axis labelled with one of the $4N$ variables. The constraints on center and edge thickness of individual lens elements, and of real glass elements, restrict the constructible lens systems to a finite subspace of the configuration space. This subspace is denoted by C , and a point within it by c . This notion for the configuration space is of course widely employed.

Our definition of a performance space, on the other hand, is a novel one. It requires a prior definition of a performance objective function (POF), with two essential properties. First, for any assignment of a specific design problem, it must provide, by its numerical values, an ordering of the relative quality of every pair of lens system configurations that might come under consideration during the design process. (We intend, in fact, more than this: that the numerical value of the POF be the ultimate measure of the quality of a configuration proposed as a solution of the design problem, and that no

post-design evaluation by other criteria be appropriate or necessary.) Second, it must be sufficiently general so that any design problem within a broad class of design problems can be identified as a particular case of the general form.

We follow the common practice of defining the POF as a sum of weighted positive terms. This sum is organized into a hierarchy of types, with weighting factors, w_i , normalized at each level in the hierarchy. The structure of the POF will only be sketched. Our scheme has, at the primary level:

$$POF = w_q(\text{Image quality terms}) + w_c(\text{Lens cost terms}).$$

We require, $w_q + w_c = 1$. At the next level, the image quality terms, for example, take the form: (Image quality terms) = $w_r(\text{resolution terms}) + w_d(\text{distortion terms}) + w_i(\text{intensity terms})$. Here again we set, $w_r + w_d + w_i = 1$. The resolution terms for example, at the next level, are to be based on the contrast ratios determined by the modulation transfer function of the system configuration. These terms comprise inclusive sampling sets of image spatial frequencies and orientations, optical wavelengths, and image field and aperture stop positions, each with its own distributions of weight factors. We emphasize that every term which potentially may be given a non-zero value in some design problem must be present in the POF.

The generalized simulated annealing method for finding the global minimum of the POF is most effective when the value of the POF tends to zero as the design approaches perfection. Thus each individual term at the lowest level in the POF is to be a monotonically increasing function of the difference between value of that particular property obtained for the actual configuration, and the theoretically achievable value.

With a POF of this general form, any set of desired performance specifications within a broad class corresponds to an appropriate assignment of weight factors. In this way we have expressed a "universal" POF as a linear expansion in an appropriate set of basis functions (the individual terms), with weight factors as expansion coefficients.

We now define the variables of the performance space, to be the set of weight factors $w = \{w_i\}$, of the POF. Because the individual terms of the POF, say f_i , are functions of the configuration variables, collectively denoted by c , the $POF = \phi(w, c) = \sum w_i f_i(c)$, provides a connection between the configuration space, C , and the performance space, W .

While a variety of useful mappings between W and C can be defined, of primary interest is the optimum design mapping (ODM). A design problem is defined by stipulating a point, w , in W . The calculation of $\phi(w, c)$ for some trial configuration, c , provides an evaluation of the quality of that configuration for the performance specification, w . There exists a $c = c^*$ (possibly not unique), for which $\phi(w, c)$ takes its unique global minimum value. The correspondence, $c = c^*(w)$, defines the ODM. So defined, the ODM induces a topological structure on the performance and configuration spaces; that structure will be exploited in the ongoing employment of the "intelligent" lens design problems.

We use the results of our preliminary investigation¹ to illustrate the nature of the ODM and the structure induced by it. We investigated the design of two element lens systems of 1 inch effective focal length, back focal length exceeding 0.75 inches, with f-numbers in the range from 10 to 5, and the fields of view in the range 10° to 30°.

To facilitate graphical presentation of the results, the performance and configuration spaces are each condensed to two dimensions; in the actual calculations these spaces were appropriately multidimensional. Clearly, sets of weights relative to positions in the image plane can be selected in a way that specifies the field of view, θ , and weights for positions in the aperture stop can be assigned to specify the f-number of the lens system. The performance space is shown as a plane in Fig. 1, where θ and f are proxies for the complete set of weights. The configuration space is condensed to the dimensions, P_1 and P_2 , representing the optical powers of the two elements.

In our formulation, the design problems are equivalent to the determination of the image, in the configuration space, under the ODM, of the shaded region, R , in the performance space. To determine that image we designed 44 lenses. As shown in Fig. 2, the image of R consists of two disjoint regions, C_1 and C_2 ; they are distinguished by the relative positions of the positive and negative elements. These regions are the neighborhoods of the minima of the POF. They are located along the line $P_1 + P_2 = 1$, in consequence of the design specification, and the fact that optical powers are felicitous condensations of the full configuration space. Several local minima may exist in each region; the design calculations reported in Ref. 1 were not adequate to provide more detailed information. However, the generalized simulated annealing optimization method is capable of coping with such situations.

Having accumulated that much information about the ODM, we may structure the "intelligent" design code to know that in order to design a lens to the requirements which are in the region R, the initial configuration for the design optimization should lie either in C_1 , or in C_2 . Any initial configurations outside of these regions (for example configurations 1,2,3, and 4 in Fig. 2), in the present relatively simple design problems, only requires a longer optimization computation. In more complex cases, however, prior partial knowledge of the ODM will, in the "intelligent" design program, be the effective surrogate for the human expert guidance.

Having introduced and illustrated the concepts and the intended automated design procedure, we provide plausibility arguments which indicate that the situation presented above is not fortuitous but that a similar structure induced by the ODM may be expected to occur generally.

Consider $\phi(w,c)$ for some fixed w_1 , in the subspace of constructible configurations, C . In general $\phi(w_1,c)$ will have a number of local minima, not infrequently located on the boundaries of C . The smallest minimum, at c^* , is the element of the ODM for this w_1 . Now, let w change continuously along some path in W from the initial w_1 to some final w_2 . Normally, we may expect that the local minimum values of $\phi(w,c)$, as well as the c at which they are attained, will also change continuously. However, as w is changed continuously, it is also possible that new local minima may appear and existing ones disappear discontinuously. Furthermore, the smallest minimum may discontinuously exchange possession of this property with some previously larger local minimum, thus leading to a discontinuous change in c^* .

If there exists a continuous path in W connecting w_1 and w_2 , along which c^* is also continuous, we will say that w_1 and w_2 are strongly connected. The following two important properties of strongly connected points are readily deduced. (1) a complete set of mutually strongly connected points forms a connected region in W , and (2) the whole of W is completely covered by a set of disjoint strongly connected regions. From the history of the design of optical imaging systems, we may expect qualitatively that strongly connected regions in W are likely to map under the ODM into relatively small isolated regions in C , each region representing a lens type.

We are currently exploring effective means to exploit this topological structure for an intelligent lens design program. Therefore, we can only outline the general direction of our investigations.

A data base of previously solved problems will constitute a partial knowledge of the ODM. The data base will contain records of design specifications, w_k , $k = 1,2,\dots$ together with the corresponding optimum configurations, c_k , and a description as to how these configurations are distributed among disjoint strongly connected regions in W . When a new design problem, w_n , is undertaken, the immediate task is to obtain one or more promising candidate configurations, c_n , for initiation of a search algorithm which is likely to converge to an optimum solution, c_n . To do so we want to recognize with previously solved problems are most closely related to the now one. For this purpose we need a metric which expresses quantitatively the "distance" between pairs of points in W . Because we have constructed W as a normalized linear space, we will initially test the usefulness of the ordinary Euclidean metric, with linear interpolation and extrapolation as the basic tools. An experienced lens designer who compares the foregoing formal mathematical structure with his own working methods will recognize that we have only codified quantitatively certain essential aspects the lens design process, that are ordinarily done more intuitively.

Design optimization

Autonomous operation of an "intelligent" design program requires an optimization method capable of locating global extrema of functions of many variables that may have numerous local extrema and may not be smooth. A promising candidate for that application is the method of simulated annealing previously used to solve combinatorial optimization problems.^{1,3} We have generalized this method, adapted it to our purpose, and investigated its performance with applications to problems in mathematical biology (11 dimensions), in crystallography (6 dimensions), and in military sciences (18 dimensions)^{1,4}. Following is a brief description of the generalized simulated annealing method employed in our "intelligent" design program to optimize lens performance.

To be definite, we postulate that the performance optimization requires location of the global minimum of an objective function $\phi(x)$ that may have several local minima, and that $\phi(x) = 0$ at the global minimum. These restrictions are not essential and can be easily removed as discussed in Ref. 4. Here x represents an N dimensional vector $\{x_n\}$; for $N = 2$, the function may look as shown in Fig. 3.

The global minimum of the function $\phi(x)$ is located with a random walk in the space of independent variables that is biased in favor of the decreasing values of ϕ . The walk is executed with the following algorithm: Beginning at any point x^i , we choose N random numbers θ_n ($n = 1, 2, \dots, N$) from the uniform distribution $-1 \leq \theta_n \leq 1$ and convert them into the direction cosines, L_n , where $L_n = \theta_n / (\sum_1^N \theta_n^2)^{1/2}$. The end point of the step to x^{i+1} is determined from: $x_n^{i+1} = x_n^i + \Delta L_n$, where Δr is the prescribed step size. on the surface of the hypersphere $|x| = 1$. We tried both methods and found little difference in the results. At the end of the step, we calculate the change in the objective function: $\Delta\phi = \phi(x^{i+1}) - \phi(x^i)$ and accept the $(i + 1)$ th step with probability $p = 1$ if $\Delta\phi \leq 0$, and $p = \exp(-\beta\phi\Delta\phi)$ if $\Delta\phi > 0$. The fact that $p = 1$ when $\Delta\phi$ is negative biases the walk in favor of the decreasing values of ϕ ; however, because $p > 0$ when $\Delta\phi > 0$, the walk is capable of climbing out of a local minimum. The presence of ϕ^g , with $g < 0$, in the exponent ensures that the probability of accepting an upward step tends to be zero as the walk approaches the global minimum where $\phi = 0$. The performance of the algorithm is not sensitive to the value of g ; in most of our calculations we set $g = -1$.

The values of Δr and β must be selected for each objective function to ensure high probability and speed of locating the global minimum. Our experience indicates that the algorithm performs well when the value of β is adjusted so that the ratio of the number of accepted to the number of rejected detrimental ($\Delta\phi > 0$) steps varies between 0.5 and 1.0. This is accomplished by monitoring the statistics of the trials and changing the value of β as required. The random walk is terminated when a specified number of consecutive trials (depending on the dimensionality of the problem) fails to result in an acceptable step.

The performance of the generalized simulated annealing method in a two dimensional space is illustrated graphically in figures 4, 5, and 6 for three different objective functions. In each case the global minimum is at (0,0). The density of the points in the circular pattern about the origin indicates the number of trials that failed to produce an acceptable step; the global minimum is taken to be at the center of the circle.

The application of the generalized annealing method does not require calculations of the gradients of the objective function; therefore it is more efficient than the standard optimization methods (that may be able to find only a local minimum) even though it may require more function evaluations. We have several ideas for improvements; these will be investigated in future applications.

Automated lens design program

In this section, we describe how we expect our program to work when completed. We envisage six principal parts of the program and point out any connections with "artificial intelligence".

- 1) A procedure control program: It would, in part, imitate the best aspects of the general methods used by skilled human designers, with some improvements and extensions, but with decidedly less flexibility.
- 2) A single general proper merit function: This involves the computation of the performance objective function, which is the merit function.
- 3) A suite of merit function evaluation programs: These would calculate the merit function at each of several levels of approximation and computational speed, as appropriate to the stage of the progress of the overall problem.
- 4) An optimization algorithm: In our case it would be the generalized simulated annealing method. Using this method, the search for an optimum solution would be initiated with the coordinates of a configuration, and the search would encompass any nearby local minimum of the merit function. It has been pointed out by the authors in Ref. 2 that optimizing using simulated annealing provides "an intriguing instance of artificial intelligence in which the computer has arrived almost uninstructed at a solution that might have been thought to require the intervention of human intelligence".

5) A dynamic data base: This would be a file of information on previously worked problems. Each record in the file would contain three kinds of data -- the coordinates in performance space; the configuration coordinates of all the local minima found; and pointers to any other performance space records to which it has previously been found strongly connected.

6) A configuration initializer: This would compare the performance space coordinates of the problem currently being worked with records in the database, and on the basis of "distances", and of actual or potential strong connectedness, would generate a sequence of trial performance space coordinates and initial configurations for the minimizing algorithm. Creative experimentation will be necessary before any more specific description of this crucial part is possible. The "artificial intelligence" of the program, will be concentrated here.

The current status of our work, as well as future work are described in the next section. Table 1 compares the procedure used an experienced lens designer and that proposed for our program. It can be seen from the table that we have only codified quantitatively, certain most important aspects of the lens design process that are ordinarily done more intuitively.

Current work and future work

Current efforts are concentrated on two aspects among the six that we feel are needed for a successful implementation of the automated lens design program: a procedure control program and the minimization algorithm.

In the area of procedure control program, Drs. Dennis Roszbach and George Lawrence of Applied Research have developed a prototype controller to automatically determine the optimum of a two parameter lens, for example, the landscape lens. This prototype controller, which is almost complete, will have the capability to create input, change table, and diagnostic decks for the version of ACCOS V* owned by the Los Alamos National Laboratory. It can transfer control to and from ACCOS and can read and interpret the diagnostic decks. Currently, it evaluates the merit function values returned from ACCOS and calculates the change table values using the generalized simulated annealing algorithm. The change table is executed using the Update Lens feature of ACCOS and the generalized simulated annealing algorithm will allow user selection of variable scaling, variable step size, maximum number of steps, and beta. The prototype controller will evaluate boundary condition violations using ACCOS boundary checking routines. The merit function is the variance of the wavefront, and the controller has graphics capabilities to plot the locations of search points and make contour plots of the rectangular scan of the parameter space.

We are currently investigating the problem of the Landscape Lens using the prototype controller. Mimmac⁵ has previously investigated this problem in detail and we are studying the problem from the point of view of testing whether this approach to the procedure control program part is feasible. Even though generalized simulated annealing has been successful in other problems, we are testing it in optical design using the prototype controller. After we understand the workings of the controller and the generalized annealing algorithm for lens design better, we hope to extend the application to the case of an arbitrary number of parameters. This will enable us to attack the practical lens design problems in earnest.

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* A proprietary code of Scientific Calculations, Inc of Fishers, N.Y.

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Table 1: Comparison Of Steps In Design Process Between Current Day
Optical Designers And Automated Lens Design Program

Optical Designer's Steps	Automated Lens Design Code
1) Stipulation of E.F.L,B.F.L, F.O.V, Resolution, intensity, Distortion, Cost, and others	Stipulation of weights $\{w_i = 1,2,\dots\}$ leads to a point in performance spaces, w_0 .
2) Study of relevent designs from design, patent literature.	Database has designs, w_k . Find j to make $ w_j - w_0 $ smallest.
3) Pick an initial configuration.	Initial configuration -- c_k^* .
4) Design merit function.	P.O.F is the merit function.
5) Minimize until satisfied.	Minimize using generalized simulated annealing.
6) If not satisfied, go to 1.	If not satisfied, go to 3.
7) Evaluate system.	Most evaluation already done.

Figure 1. PERFORMANCE SPACE

Figure 2 CONFIGURATION SPACE

Figure 3. OBJECTIVE FUNCTION WITH MANY LOCAL MINIMA AND A GLOBAL MINIMUM AT (0,0); THE FUNCTION IS $\phi_1(x,y) = ax^2 + by^2 - c \cos(\alpha x) - d \cos(\gamma y) + c + d$, WHERE $a = 1$, $b = 2$, $c = .3$, $d = 0.4$, $\alpha = 3\pi$, $\gamma = 4\pi$.

Figure 4. GENERALIZED SIMULATED ANNEALING METHOD WITH $g = -1$, $\Delta r = .15$, $\beta = 3.5$. SAME FUNCTION AS ϕ_1 IN FIGURE 1. SOLID DOTS ARE ACCEPTED STEPS, OPEN SQUARES ARE REJECTED STEPS.

Figure 5. GENERALIZED SIMULATED ANNEALING METHOD WITH $g = -1$, $\Delta r = 0.15$, $\beta = 3$. THE FUNCTION IS $\phi_2(x,y) = ax^2 + by^2 - c \{\cos(\alpha x)\}\{\cos(\gamma y)\} + c$, WITH THE COEFFICIENTS AS IN FIGURE 1.

Figure 6. GENERALIZED SIMULATED ANNEALING METHOD WITH $q = -1$, $\Delta r = 0.15$, $\beta = 3$. THE FUNCTION IS $\phi_3(x,y) = ax^2 + by^2 - c \cos(\alpha x + \gamma y) + c$, WITH THE COEFFICIENTS AS IN FIGURE 1.