EVOLUTIONARY DESIGN OPTIMIZATION OF A MICROOPTICAL COLLIMATION SYSTEM

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ABSTRACT: The production of specimen for microsystems or microcomponents is both, time and material-consuming. In a traditional design process the number of possible variations which can be considered is very limited. Thus, in microsystem technology computer-based design techniques become more and more important - similar to the development of microelectronics. The computer aided development and optimization is based on simulation models.
This paper presents the concept of a partially automated design optimization as an application of our evolutionary optimization environment. A 2-lens-system being part of a heterodyne receiver, a microoptical communication module, has to be optimized to be as insensitive to fabrication tolerances as possible while still maintaining optimal properties of the collimation system. The optimization results obtained are compared to a hillclimbing strategy with respect to both, convergence reliability and convergence velocity.

1 INTRODUCTION

The production of specimen for microcomponents or microsystems is both, material and time consuming because of the sophisticated manufacturing techniques. In a traditional design process the number of possible variations which can be considered is very limited. Consequently, the manufacturing step should be preceded by simulations; the results of which may constitute a basis for making a laboratory specimen. Measurements conducted on laboratory specimens furnish data for comparison to validate the simulation model and to learn about the microsystems behavior as well.
Thus, in microsystem technology computer-based design techniques become more and more important - similar to the development of microelectronics. The computer aided development and optimization is based on simulation models. These must be sufficiently fast computable and need to be parameterizable. In addition they need to be accurate enough, as the quality of an optimization depends highly on the quality of the simulation model.
Systems design on the physical level by means of Finite Element Method (FEM) simulation models normally is feasible only for system components or even parts of them, because of the rapidly growing complexity of the model and the resultant long simulation times. A higher degree of model abstraction linking components can be described by analytical models, which lead to much shorter computation times with a circuit simulator. But, the disadvantage is that the accuracy of the simulation results often leaves to be desired and the analytical models themself need to be optimized by a model adaptation process. Thus, these analytical macromodels both need to be adapted to FEM component models and can be combined into system models, and then improved towards preset optimization goals, by means of a suitable search technique improving their quality. For this difficult optimization task we promote the application of evolutionary algorithms.
The techniques listed above are supported by the open tool environment **SIMOT (Sim**ulation and **O**ptimization **T**ool Environment) developed at the Institute for Applied Computer Science of the Research Centre Karlsruhe. **SIMOT** includes tools for optimization and for simulation and will on one hand support the designer to develop and optimize macromodels and on the other hand to optimize complex (micro-)systems or components [Süß et al. 1997]. The optimization tools GAMA (Genetic Algorithm for Model Adaptation) and GADO (Genetic Algorithm for Design Optimization) are based on evolutionary algorithms and are developments of our institute [Jakob et al. 1996; Gorges-Schleuter et al. 1996]. The simulators are commercial tools: an FEM simulator, an analog network simulator and Mathematica 2.0[1]. The optimizer and the simulator are loosely coupled and may be chosen depending on the problem to be solved.
Our evolutionary search technique can be used also on other design problems, for instance, in the field of optics. One example of such an application, the microoptical collimation system, is the subject of this paper. Here, we used Mathematica for the simulation of the model and GADO as optimizer. The optimization of the design of a collimation system under realistic production conditions shows how SIMOT is successfully used on a multiple objectives problem with conflicting criteria. The search space of the application is of complex nature although there are only few variables to be considered.

1. Mathematica is a registered trademark of Wolfram Research, Inc.

2 EVOLUTIONARY DESIGN OPTIMIZATION

During the design process the engineer is faced with a large search space of possible design solutions and parameterizations. The production of specimen is limited to a few only. The situation becomes better by creating a simulation model which might be evaluated by a simulator. During an optimization process many simulations with various parameter settings have to be done. As the complexity of the search space of such a simulation model becomes in general very high already if only a few input parameters are treated, manually controlled simulations for only a few design variants, as a rule, will not result in optimum systems design. In addition the manual exploration is limited and mainly influenced by personal knowledge, previous experiments, intuition of the engineer and good luck. Fig. 1a shows the conventional design process.

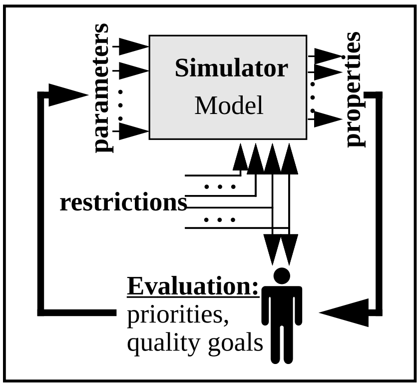


Fig. 1a: Conventional Design Process

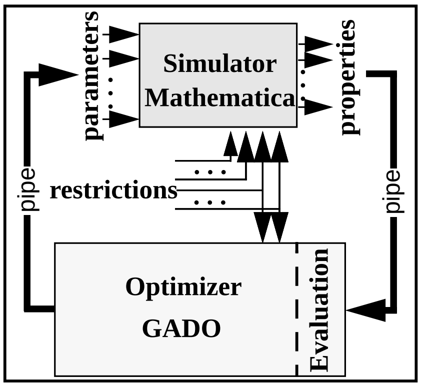


Fig. 1b: Optimization with GADO

Assuming that we are able to build a simulation model being accurate enough and parameterizable, then the engineer‘s optimization task can be supported by an automatic tool, the evolutionary optimizer GADO, that explorates and exploitates the search space of the systems parameters. This is shown in Fig. 1b.

Human activities, in this case, are the specification of the optimization parameters and restrictions and to predefine an evaluation, a description of the quality goals and priorities. Especially in case of multiple objectives being not mutually independent we cannot optimize for the quality goals separately. Consequently, the formulation of grading functions and priorities, as described below, gives the engineer the possibility to provide the optimizer with a suitable way of making its decisions.

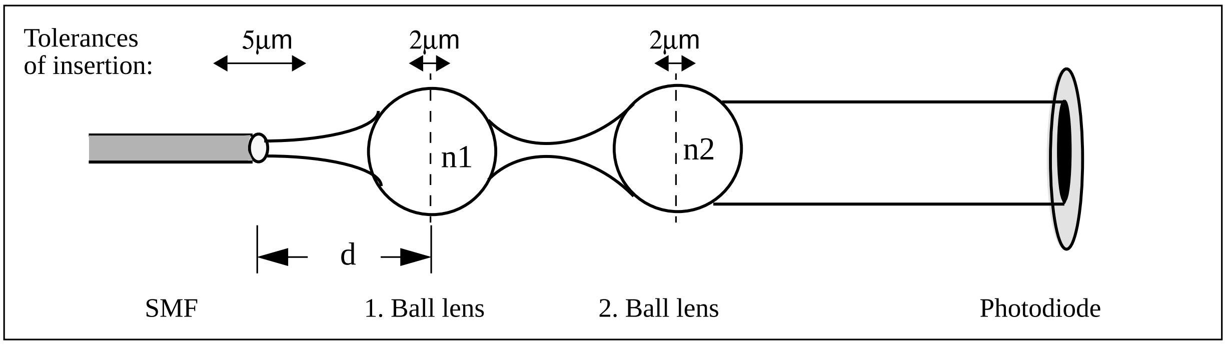
The task of the explorer is to implement an ‘intelligent‘ search focusing on promising areas of the search space, avoiding suboptima and adapting itself to the search landscape. The explorer is based on the evolutionary algorithm GLEAM (**G**enetic **Le**arning **A**lgorithms and **M**ethods) [Blume 1991] being itself based on both the Genetic Algorithms established by J. Holland [Holland 1975] and on the Evolution Strategies established by I. Rechenberg and H.-P. Schwefel [Rechenberg 1994; Schwefel 1995]. The GLEAM concept has been extended by a spatially structured population approach [Gorges-Schleuter 1994] and approved its performance in such different areas of application as machine learning [Jakob et al. 1992], robot path planning [Blume et al. 1994], resource planning and job shop scheduling [Blume et al. 1993].

The representation of an individual is a list-like hierarchical data structure. The elements of the data structure depend on the actual application. The hierarchy may be used to treat parts of the data structure as a unit, termed section, and thus prevent them from being separated by the crossover operators or to hide them completely thus prevent them from being modified by any of the genetic operators.

The mutation operator is inspired from its counterpart in evolution strategies in the sense that small variations of genetic values are more likely than larger ones. GLEAM allows the usage of any arbitrary alphabet for the internal representation. Assuming that the elements of the alphabet (i.e. the values a certain parameter can take) are sorted by some criteria, we create before applying the mutation operator a division of the range of values into classes. By mutation a change of the current value to a random value within the nearby classes is very likely and this probability shortens with the distance of a class as defined by a prespecified step function. There are various crossover operators implementing traditional n-point crossover and uniform crossover as used in genetic algorithms and crossover operators respecting the creation and existence of sections, which itself underlay the evolutionary process.

Each genetic operator may be independently activated on a percentage basis. Whenever an operator is chosen, a new offspring is generated. Thus, if several genetic operators have a percentage of choice greater than zero, there will be a chance that more than one offspring will be generated from one pair of parents. The resulting set of descendants will be evaluated and only the best will be considered to be included into the population as described by the survival rule.

The total population of individuals is distributed in a geographic space. In the following experiments with GADO a linear ring structure has been chosen and the selection process acting through both, mate selection and survival rule, is limited to locally nearby individuals. The size of the neighborhood of any individual is set to 8, thus each individual has only knowledge of its four neighbors to the right and left, respectively. Each individual and its partner being chosen by local linear ranking produce offsprings by means of the genetic operators. The descendants are evaluated and the best of them is compared with the individual and replaces it immediately, but only if the offspring is better than the weakest in its neighborhood and with the exception of those individuals being the locally best, then the offspring must be better than the individual itself (local elitism) [Gorges-Schleuter 1994]. This process is continued until a termination criterion is reached.



Distance between lenses:		[80...1400µm]
Illumination:	$\frac{\text{diameter of the beam at the photodiode}}{\text{diameter of the photodiode}}$	[80...100%]
Stability:	$\frac{\text{min diameter of the beam at the photodiode}}{\text{max diameter of the beam at the photodiode}}$	[>90%]
Waist position:	position of the collimated beam waist	[4000...4600µm]

Fig. 2: Geometry of the collimation system made up of a single mode fiber (SMF), two ball lenses and a photodiode. The optimization parameters are n1, n2 and d. The tolerances of insertion due to the positioning of the devices are given in the top row. The bottom box shows the definition of the optimization criteria and the range of acceptable values.

3 OPTIMIZATION OF A MICROOPTICAL COLLIMATION SYSTEM

The design of systems incorporating a laser beam, as many microoptical applications do, mostly require the modification of the “raw“ beam. The beam must be expanded, refocused and collimated. These modifications can be performed by using lenses, mirrors or prisms [O‘Shea 1985]. The system described here uses two microoptical ball lenses. The first lens is used to refocus the beam from a single-mode fiber (SMF) so that the second one is able to collimate the refocused beam in the desired way. The geometry of the 2-lens system is shown in Fig. 2.

In the ideal case of geometrical optics, under certain restrictions, there does exist an unlimited possibility of combinations of the focosing geometry to generate the specified irradiation. Unlike this ideal case, also tolerance effects are to be considered which arise from the incorporation of optical elements into prefabricated LIGA structures [Bley 1991](Fig. 2 top). These insertion tolerances affect the beam width at the photodiode and also affect the location of the beam waist. The optimization task is to determine a collimation system which is as insensitive as possible to the expected inaccuracies, due to incorporation of the individual elements.

The systems parameters which can be varied in the optimization process are the refractive indices of the two ball lenses n1 and n2 in the range of 1.4 to 2.0, and a value z in the range of 1.0 to 2.0. Using z and the focus of the first ball lens we compute the distance of the single-mode fiber to the first lens as d = z*(n1*R)/(2*(n1-1), where n1 is the refractive value of the first lens and R=450µm is the radius of this ball lens.

The optimization criteria are stability, illumination, position of the beam waist, and distance between the two lenses. The definition of these values as well as the range of valid values is given in Fig. 2. The optimum values are 100% for stability, 90% for illumination, 4300µm for the beam waist position and the distance between the lenses should be preferably be above 100µm and below 1000µm.

The collimation system is modelled in the limit of geometrical optics and simulated with Mathematica, where the extreme values of the displacement of the systems components are used to perform the necessary simulations for a single design evaluation. The amount of computing time consumed for each evaluation is about 1 sec on a Sparc Ultra 1. Using the simulation outcome we compute the absolute value of the optimization criteria.

The multiple objective optimization is done by using grading functions assigning to each absolute value a grade (N) between 0 and 100000. Fig. 3 shows these grading functions at hand of the illumination and stability criteria. For example, for the illumination criterion 90% are optimal and a value of up to 95% is regarded as acceptable; if the simulation detects an underfill or overfill at the photodiode the outcome is degraded exponentially. All grades are then weighted, as specified by the weight functions given by the engineer, and summed up. In our setting a total maximum of 100000 might be reached, but, only in case of mutual independent criteria.

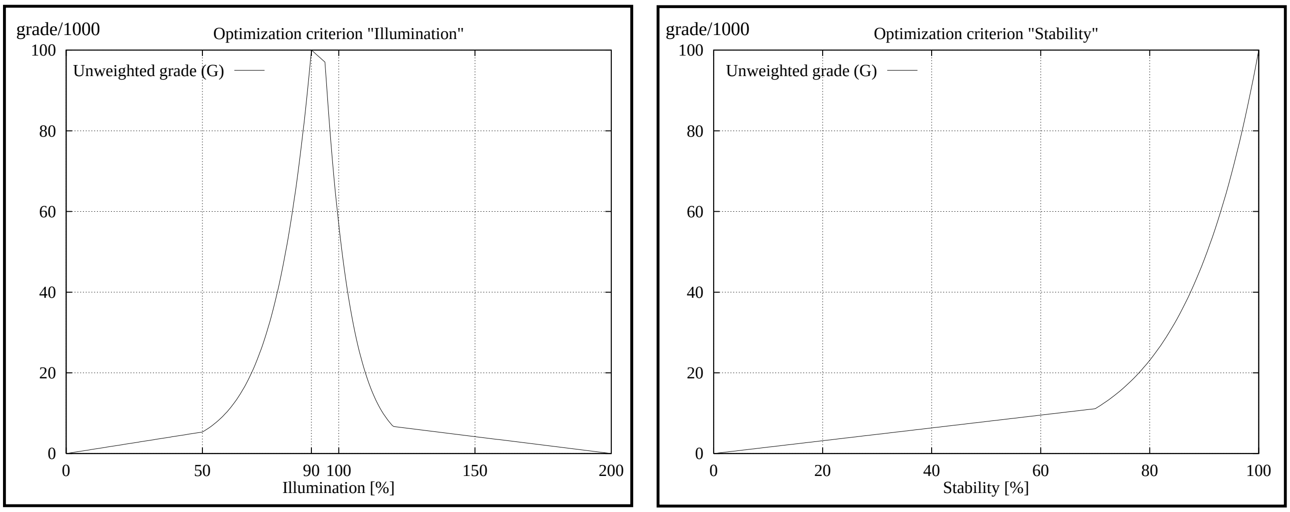


Fig. 3: Grading functions for (left) illumination and (right) stability.

4 RESULTS

Our first simulations of the collimation system showed that we were not able to find satisfactory design values by a simple Monte-Carlo approach. Scatterplots of solutions of optimization runs done with respect to a single criterion only showed that the optimization criteria are conflicting and the combined search space seems to show a fractal nature. Especially, the demands on stability are hard to fulfil.

A hillclimber was used next. Starting from a random initial setting one of the parameters is chosen and optimized until no further improvement of this parameter is possible, then the next one is chosen and optimized and this is repeated until no further improvement is possible. The number of evaluations performed until this strategy converges differs in a wide range of 2000 to 42000. The quality gained is given in the first row of Figure 4. The best solution found has n1 = 2.0, n2 = 1.58, and z = 1.10, which results in a distance of the single mode fiber to the first lens of d = 495µm. The other optimization values are a stability of 90.3%, an illumination with small overfill of 90.7% and a waist position at 4294.3µm.

The question arises how good an “intelligent“ search might do. The termination criterion of the evolutionary algorithm GADO is set to an upper limit of 36000 evaluations. The population size is varied between 60 and 210; all other settings are fixed and set as described in section 2. For each population size 30 runs are performed. Figure 4 gives the optimization results for the various population sizes. We recorded how often a grade (G) of 80500 was reached (Fig. 4, column 1) and the number of evaluations needed to obtain this quality (Fig. 4, column 2-3). A population size of 120, which results in about 360 descendants per generation, is very reliable. The last three columns of Fig. 4 give the minimum, maximum and average grade. Larger populations give even better results, but at the price of an increase of evaluations needed.

The best solution of our evolutionary algorithm GADO got a grade of 81031. This solution has n1 = 1.597, n2 = 1.548, and z = 1.316, which results in a distance of the single mode fiber to the first lens of d = 792µm. The other optimization values are a stability of 91.22%, an illumination of 90.00% and a waist position at 4300.1µm. This means the evolutionary algorithm produced a very good and especially stable solution.

	G > 80500	min. evals	av. evals	min. grade	max. grade	av. grade
Hillclimber	0	2161	10800	72340	79068	75362
Evo, P=60	21 of 30	1147	12217	79549	80827	80508
Evo, P=90	21 of 30	434	15345	79765	80879	80523
Evo, P=120	28 of 30	563	6657	80273	80946	80661
Evo, P=150	29 of 30	723	6603	80437	81034	80631
Evo, P=180	29 of 30	944	7586	80356	81022	80629
Evo, P=210	29 of 30	1061	8213	80463	80992	80644

Fig. 4: Comparison of the hillclimber with the evolutionary algorithm with various population sizes.

5 CONCLUSIONS

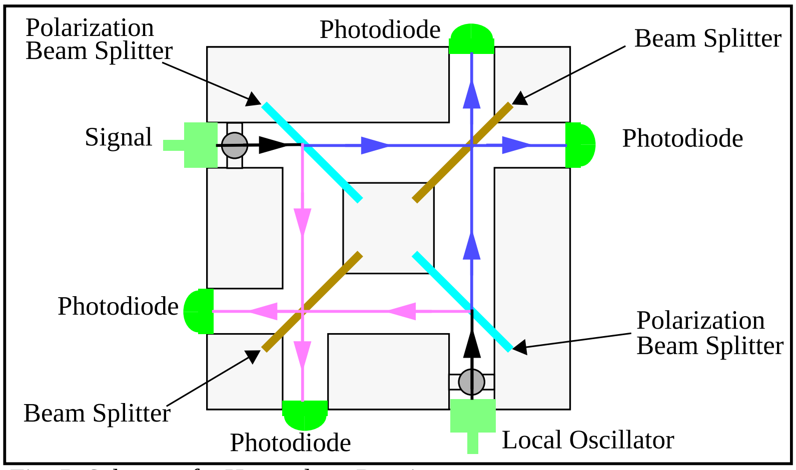


Fig. 5: Scheme of a Heterodyne Receiver

The optimization of the collimation system by using a method of optimization which takes into account in its calculations only the immediate vicinity of the point under consideration gave only weak results on our multi-modal problem. The geographically structured population search with local interaction rules only done by the evolutionary algorithm found high quality solutions (at least near-optimal) with high convergence reliability.
Currently a simulation model of the collimation system based on wave front propagation is considered; the simulation times then rise to 30 sec and more. To reduce the number of simulations while still maintaining the high convergence reliability we investigate besides parallelization of the evolutionary algorithm the incorporation of previous knowledge acquired by EAs with a small population size.
The collimation system simulated and optimized in this paper with SIMOT is part of a heterodyne receiver. The basic idea behind this microoptical communication module is to mix the received signal coherently with another optical wave before it is incident on the photodetector. The optical wave is generated locally at the receiver by using a narrow-linewidth laser (the so called local oscillator). In the case of heterodyne detection the local oscillator frequency is chosen to differ from the signal-carrier frequency such that the intermediate frequency is in the microwave region.
Beside the optical effects like e.g. diffraction and misalignment of the passive or active optical components there are environmental effects that influence the performance of the receiver. These effects are mainly induced by local temperature variations caused by thermal radiation of the surrounding electronics or by variation of the ambient temperature. Therefore not only an optical simulation is needed to describe this system but also a simulation to these environmental effects.

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