Solving a highly multimodal design optimization problem using the extended genetic algorithm GLEAM

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Abstract

In the area of micro system design the usage of simulation and optimization must precede the production of specimen or test batches due to the expensive and time consuming nature of the production process itself. In this paper we report on the design optimization of a *heterodyne receiver* which is a detection module for optical communication-systems. The collimating lens-system of the receiver is optimized with respect to the tolerances of the fabrication and assembly process as well as to the spherical aberrations of the lenses. It is shown that this is a highly multimodal problem which cannot be solved by traditional local hill climbing algorithms. For the applicability of more sophisticated search methods like our extended Genetic Algorithm GLEAM short runtimes for the simulation or a small amount of simulation runs is essential. Thus we tested a new approach, the so called *optimization foreruns*, the results of which are used for the initialization of the main optimization run. The promising results were checked by testing the approach with mathematical test functions known from literature. The surprising result was that most of these functions behave considerable different from our real world problems, which limits their usefulness drastically.

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 performed 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.

In this paper we report on the design optimization of a *heterodyne receiver* which is a detection module for optical coherent communication-systems that mixes the carrier wave coherently with a locally produced signal of slightly different frequency. The collimating lens-system of the receiver is optimized with respect to the tolerances of the fabrication and the assembly process and to the spherical aberrations of the lenses. It is shown that this is a highly multimodal problem which cannot be solved by traditional local hill climbing algorithms.

We used our **SIM**ulation and **O**ptimization **T**ool Environment **SIMOT,** see Jakob et al. [1], based on the extended Genetic Algorithm **GLEAM** (**G**enetic **Le**arning **A**lgorithms and **M**ethods, see Blume [2]) instead to obtain high quality results. As the runtime for a simulation is in the range of about half a minute on an Ultra Sparc 2 the required number of simulations is essential to the applicability of our heuristic search method. Thus we tested a new approach, the so called *optimization foreruns*, the results of which are used for the initialization of the main optimization run. To achieve reliable test results a set of runs must be performed for every parametrization of the forerun concept. To do this within a reasonlable amount of time a simplified and therefore much faster model was used which dropped the effects of wave field propagation. The promising results were checked against mathematical test functions known from literature, before we applied the method of foreruns to the actual optimization problem.

SIMOT supports the designer to develop and optimize simulation models as well as to optimize complex (micro-)systems or components. It includes optimization tools and simulators. The optimization tools GAMA (Genetic Algorithm for Model Adaptation) and GADO (Genetic Algorithm for Design Optimization) are based on GLEAM and are developments of our institute. The simulators are commercial tools: an FEM simulator, an analog network simulator and Mathematica[1]. The optimizer and the simulator are loosely coupled and may be chosen depending on the problem on hand. For the optical system described further on we used Mathematica for the simulation 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

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

search space of the application is of complex nature although there are only few variables to be considered.

2 Evolutionary Design Optimization

During the design process the engineer is faced with a large search space of possible design solutions and parameterizations. Building models is limited to a few only. The situation becomes better by creating a computer model which might be evaluated by a simulator, see Fig 1a. During an optimization process many simulations with various parameter settings have to be done. The complexity of the search space is in general high so that a manual exploration is limited and mainly influenced by personal knowledge, previous experiments, intuition of the engineer and good luck. An optimal system design might not be expected under these conditions.

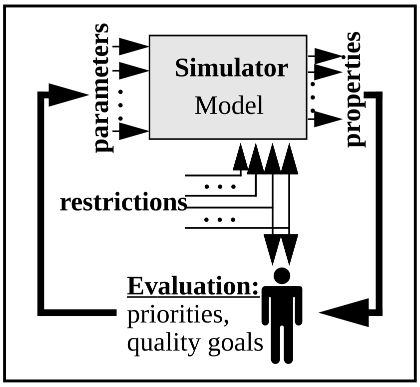


Fig. 1a: Conventional Design Process

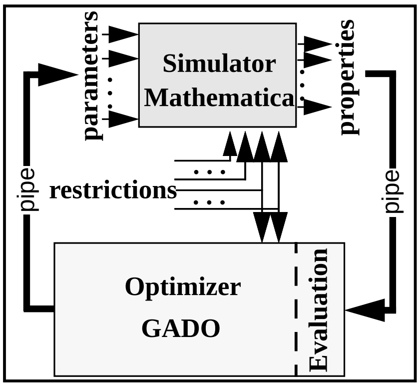


Fig. 1b: Optimization with GADO

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 evolutionary search techniques explorating and exploitating the search space, see Fig. 1b. The engineer’s task is now the specification of the optimization parameters and restrictions and the formulation of the criteria of optimization. In case of multiple objectives being not mutually independent we cannot optimize for the quality goals separately. 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 optimizer is to implement an ‘intelligent‘ search focusing on promising areas of the search space, avoiding suboptima and adapting itself to the search landscape.

2.1 The GLEAM Concept

The GLEAM concept has been extended by a spatially structured population approach, see Gorges-Schleuter [3] and approved its performance in such different areas of application as machine learning (Jakob et al. [4]), robot path planning (Blume et al. [5]), resource planning and job shop scheduling (Blume et al. [6]).

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.

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. 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 neighbourhood of any individual is set to 8, thus each individual has only knowledge of its four neighbours 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 neighbourhood and with the exception of those individuals being the locally best, then the offspring must be better than the individual itself (local elitism), see Gorges-Schleuter [3]. This process is continued until a termination criterion is reached.

2.2 Concept of Foreruns

Two different types of experiments were performed: the first type consists of a single more-or-less "large" population while the second one is split into a forerun and a main run. The forerun consists of small sized pre-populations performing only a small number of generations. The final best individuals obtained from the foreruns are used to initialize the main population. The idea of combining foreruns followed by a main run is inspired by the promising results of using previous knowledge for the initial population reported by Jakob et al. [4] and shall hopefully reduce the number of required evaluations.

2.3 Local Hill Climbing Algorithm

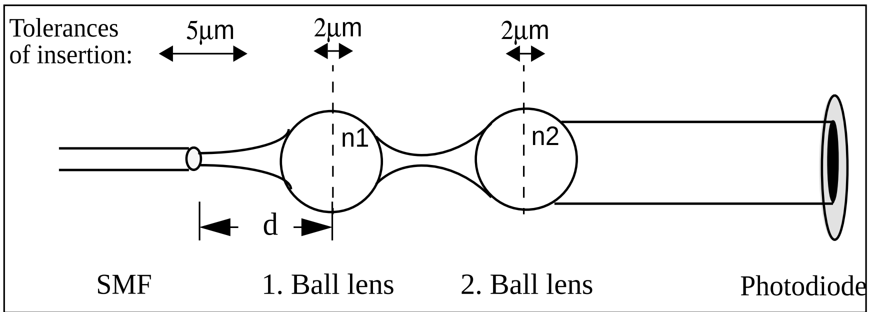
Our simple derivation free hillclimber (Gauss-Seidel-Strategy with fixed step size for the line search and multiple restart) starts from a random initial setting of the parameters. One of them is chosen and optimized until no further improvement of this parameter is possible, then the next one is chosen and optimized and this is repeated until no further improvement is possible.

3 The Task: Optimization of a Microoptical Collimation System

The design of systems incorporating a laser beam, as many microoptical applications do, mostly requires the modification of the “raw“ beam. The beam must be properly modified, e.g. expanded, refocused and collimated. This modification can be performed by using lenses, mirrors or prisms, see O’Shea [7]. For our application, the collimation system, we will use two microoptical ball lenses. The geometry of the 2-lens system is shown in Fig. 2.

The beam as it comes out of a single mode fiber is refocused by the first lens and then collimated by the second one in order to position the collimated beam waist at the location of the photodiode. In an ideal case of geometric optics it is possible under some restrictions to derive for each lens with refractive value n1 a second lens with refractive value n2 so that the required irradiation is yielded. In reality, we need to place the elements into prefabricated LIGA structures, see Bley et al. [8], and this can only be done with some tolerances. These tolerance values of insertion are given in the top row of Fig. 2.

These variations of the placement influence the position of the beam waist and the diameter of the beam at the photodiode. The optimization task is to determine a collimation system being as insensitive as possible with respect to the variances of insertion. The optimization parameters are the refractive values n1 and



Distance between lenses:		[100...1000μm]
Illumination:	$\frac{\text{diameter of the beam at the photodiode}}{\text{diameter of the photodiode}}$	[90..95%]
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	[4300μm]

Figure 2: Geometry of the collimation system. The bottom box shows the definition of the optimization criteria and the range of success values.

n2 of the ball lenses 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 fiber to the first lens as

$$d = \frac{z \cdot n1 \cdot R}{2 \times (n1 - 1)}$$

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, waist position 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 simulated with Mathematica, where the extreme values of the displacement are used to determine the number of necessary Mathematica simulations for one design evaluation. 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% is optimal and a value of up to 95% is regarded as a success; if the simulation detects a further underfill or overfill at the photodiode the outcome is degraded exponentially. A solution is regarded as a success, if the values of Fig.2 are fulfilled and with increasing stability values successful runs are ranked higher. 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 in case of mutual independent criteria.

We used two versions of the simulation model: The original model takes both into account, the insertion tolerances as shown in Fig. 4 as well as the spherical aberrations as reported by Sieber [9], while the simplified one ignores the spherical aberrations and uses the simplified insertion tolerances as shown in Fig. 2. The reason for this are the much shorter evaluation times of the simplified model of about 1 second compared to about 35 seconds of the original model. Thus comparative

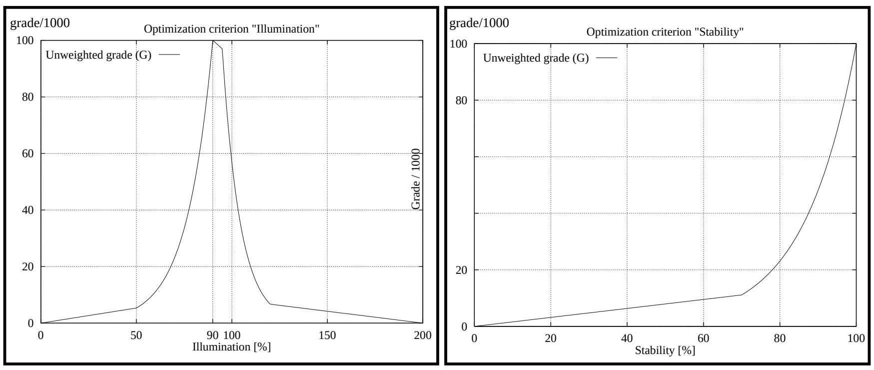


Figure 3: Grading functions for illumination (left) and stability (right) .

studies could only be done using the simplified model. The reason for the much more expendable model is that numerous studies ([10], [11]) show that spherical aberrations are the optical effect dominating the performance of microoptical systems with ball lenses as imaging elements.

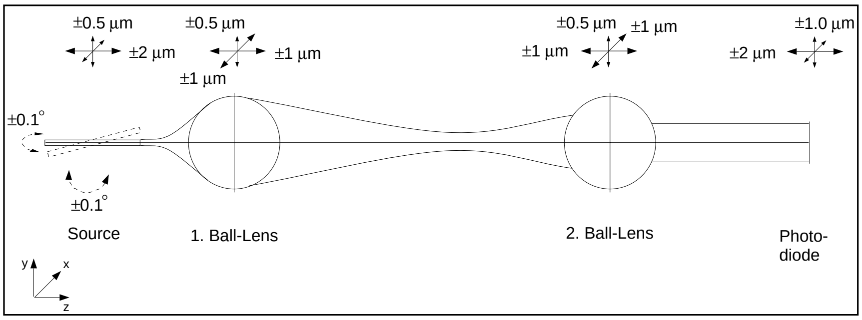


Figure 4: Insertion tolerances of the model considering spherical aberrations.

4 Results

4.1 Design Optimization Using the Simplified Model

The hillclimber (HC) produced widely differing solutions depending on the randomly chosen start values. Especially, the demands on stability were hard to fulfill. This indicates the highly multimodal nature of the problem. The number of evaluations needed until this strategy converges differs in a wide range of 2000 to 42000 yielding in a range of quality grade values between 72340 and 79068. Details of the best solution found are reported in section 4.3.

For reasons of comparability the runs using GLEAM were limited to an upper limit of about 36000 evaluations. For each setting (job) 40 runs were done and the quality threshold was set to a grade of 80500, which is not the best we could achieve (the best solution found has a quality of 81031), but a pretty good design quality. We recorded how many runs meet this requirement and how many evaluations were used by the “good” runs. The results are shown in Table 1.

As none of the HC runs meet the target grade the figures for the number of evaluations are calculated on the base of all runs and not of only the “good” ones as with the rest of the table. It is obviously that the HC approach is not sufficient to tackle the task.

As expected GLEAM delivers with single runs (GS) reliable good results with increasing population size. Thus we can take the GS7 job as a reference for the jobs with foreruns (GF). The foreruns of all GF jobs were done using t a population size of 16 each. Neither GF1 nor GF4 are considered further due to the low number of successful runs. GF2 delivers reliable results with 21% less average evaluations than GS7. Further reductions to 46% can only be achieved by a slightly loss of re-

Table 1. Results from hillclimber (HC), GLEAM with single runs (GS) and foreruns (GF).

Job	Foreruns		Main Population Size	# of Successfull Runs	Speed-up wrt GS7 [%]	Evaluations of Fore a. Main Runs		
	Number	Gen.				Median	Average	Variance
HC				1		6483	10986	15354
GS1			60	28		2570	3844	3765
GS2			90	28		4472	5845	6782
GS3			120	36		4295	4802	3905
GS4			150	39		4231	5252	4799
GS5			180	39		5825	6276	3989
GS6			210	39		5858	6644	4020
GS7			240	40		7674	7743	4282
GF1	10	10	60	33	41	4082	4601	3433
GF2	20	10	60	40	21	5719	6113	4291
GF3	10	20	60	39	46	3407	4147	3168
GF4	10	10	90	37	33	5343	5195	3301
GF5	10	20	90	39	30	3193	5448	4792

liability as shown by GF3. Thus we decided to proceed with the settings of GF3 for the optimization of the original model.

4.2 Design Optimization Using the Original Model

The first 2 rows of Table 2 compare the results achieved applying the hill climbing algorithm (HC) and GLEAM to the simplified model (GSM). Although there are comparable results the appendant optical systems are completely different. As shown in the third row the best solution using the more sophisticated original model (GOM) results again in a different optical system as expected. Due to the different nature of the model other optimization criteria had to be used describing similar properties as with the simplified model.

Table 2. Comparison of the Optimization Results

	n1	n2	d	Illumination	Stability	Waist Pos.
HC	2.00	1.58	495	90.7	90.28	4294
GSM	1.60	1.55	792	90.0	91.22	4300
GOM	1.99	1.65	450			

4.3 Benchmark Functions

In order to check our approach of foreruns we decided to apply the concept to some commonly used multimodal benchmark functions, see Bäck [12] and Rechenberg [13]: Shekel's Foxholes problem, Ackley's function, a fractal function, the generalized Rastrigin function and Rechenberg's truly multimodal test problem. The results using various population sizes are shown in Figure 5. All test functions except of the fractal function show a roughly linear behavior of the computational load with respect to the population size and work still with extreme small populations. This differs significantly from the design optimization task and the other real world problems mentioned in section 2.1. For real world problems it is typical that there exists a problem dependent lower limit of the population size for reliable results. Increasing this size the amount of evaluations as well as the variance decreases until a minimum is reached and afterwards the computational load increases again. This minimum span can be regarded as the *best working area* of our heuristic search method. As Fig 5 shows this area is for the design problem on hand a population size of about 150 and for the fractal function of about 200. The decrease of the two plots at their left end with very low population sizes is caused by failed runs which have been stopped due to premature convergence.

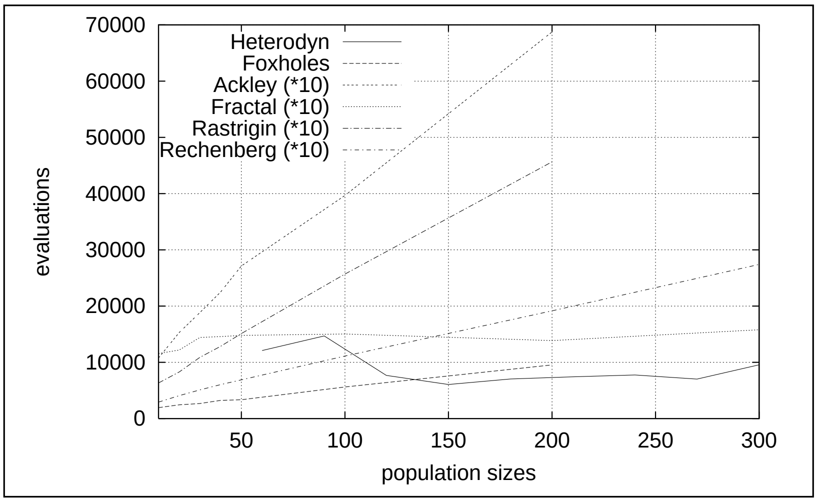


Figure 5: Beavior of some benchmark tasks vs. the heterodyn receiver task.

A benchmark or test function is only as good as it mimicks the behavior of the original task. Thus all the test functions except of the fractal function must be rejected as benchmarks for evolutionary optimization methods in particular and presumable for heuristic general purpose optimization algorithms in general. They can be used only as a first check for testing algorithms but not for performance tuning or as a method of comparison.

5 Conclusions and Outlook

We have shown that the optimization task of the heterodyne receiver is despite of the few parameters of such complex nature because having regarded to the insertion tolerances that the application of our evolutionary search method is advisable. A simplified but fast model of the receiver was used to investigate the concept of foreruns in detail. The obtained parameter settings were used to optimize the original model taking spherical aberrations and more fabrication and insertion tolerances into account. Finally we analyzed the usefulness of some frequently used benchmark functions and concluded that most of them are of very limited usability.

Currently an even more sophisticated model is under development which will include then the complete receiver with wave superpositioning and thermal effects.

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