Project Description: Multi-Objective Optimization in Imaging Optics

Overview

This project is concerned with exploring and developing multi-objective optimization strategies in the context of imaging optics. The aim is to develop problem-specific strategies that focus on the multi-objective aspect of imaging optics. Especially, we would like to investigate optical systems by finding trade-off solutions, allowing to make choices for the final design and get a better understanding of the underlying design process.

Introduction

Imaging optics involves the design and optimization of imaging systems. These systems may be composed of lenses (e.g. cameras) or mirrors (e.g. telescopes) in various fields of application. The aim of imaging systems is to most accurately capture and reproduce an image. This is equivalent to the task of focusing all light coming from one point of an object plane to one point of an image plane. This would be the ideal case. Depending on the problem at hand and the corresponding degrees of freedom, we observe errors of different type that are called aberrations in optics (e.g. monochromatic aberrations like defocus, coma, astigmatism, ...). Two examples are given in Figure 1. Aberrations are typically quantified using an expansion of the optical map, mapping coordinates in the object plane to coordinates in the image plane, or measured based on the observed spot size.

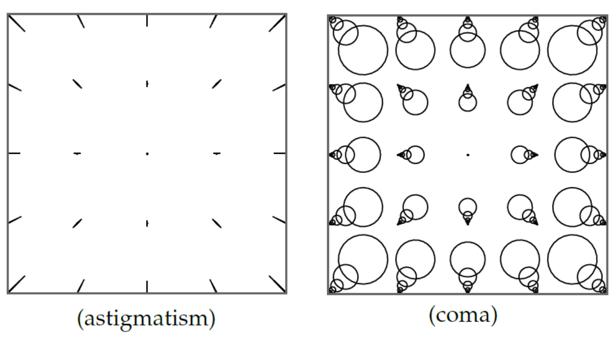

Figure 1: Spot size diagrams for astigmatism (left) and coma (right) showing the effect of these aberrations for light rays emerging from 25 different object points.

Multi-objective optimization problems deal with the optimization of a vector-valued objective function. If objective functions are conflicting, there is no single optimal solution. Instead, it can be interesting to find a representative set of trade-off solutions using the notion of Pareto optimality (see Figure 2). Multi-objective optimization methods can be categorized as direct methods and scalarization methods. Direct methods find a set of Pareto optimal solutions in one optimization procedure, typically using heuristics. Opposed to that, in scalarization methods the multi-objective problem is transformed into several single-objective optimization problems. The most intuitive strategy is to define a weighted sum of objective functions. However, it is well known that a weighted sum method has several drawbacks. First of all, the choice of weights and the strategy for altering the weights to find different trade-off solutions are not straightforward. Usually, there is no direct relationship between the weights and the obtained trade-off. A common observation is that, even when altering weights in a systematic manner, solutions will cluster at certain regions in objective space. Furthermore, the full set of optimal solutions can only be found for convex optimization problems.

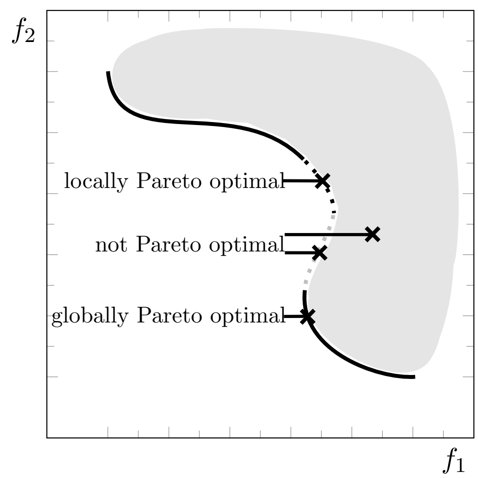

Figure 2: Depiction of Pareto optimal solutions in objective space for two objectives f_1 and f_2: The grey region is the feasible objective space. The bold line is the Pareto optimal front, the set of all Pareto optimal solutions. Solutions on the black, dashed line are only locally Pareto optimal.

Multi-objective optimization problems in imaging optics arise on a more general level when considering the interplay of quality, cost and manufacturability. But already when only considering imaging quality there can be competing performance measures associated to it. Accordingly, a typical goal in imaging optics is to minimize different types of aberrations. The ***state of the art*** of this process is the following: An optical designer will weigh the significance of different objectives to form a weighted sum of, e.g., aberrations to be minimized. When using typical optical design software like CODE V or Zemax, the user is restricted to choosing a single objective function (typically the spot size) and several constraint functions. However, this requires expert knowledge and will only provide a single design solution. Moreover, when using a weighted sum of objectives not all trade-off solutions can be necessarily found by minimizing a convex combination of objective functions. Additionally, using the spot size as a performance measure will not give insight in the different types of aberrations.

There exists few literature on multi-objective optimization focusing on minimizing aberrations, mainly based on (meta-)heuristic approaches: An epsilon-dominated multi-objective evolutionary algorithm is employed in [5] for a Petzval lens to investigate spherical aberrations, distortion and a nonlinear objective function of other types of aberrations. In [6], the popular NSGA-II method is employed to minimize different components of wavefront aberrations in a telescope. [7] extends the NSGA-II method in the context of lateral and wavefront aberrations. As already stated above, heuristics usually require many function evaluations. Therefore, we would like to investigate the use of scalarization methods in this context.

Research Goals and Challenges

The general ***goal***, as formulated in the overview is to explore and develop new multi-objective optimization strategies in the context of imaging optics.

Imaging optics will bring some interesting ***challenges*** to the development of multi-objective optimization methods:

- The problem formulation has to be done carefully. This requires the modeling of the optical system, the definition of suitable objective functions and constraints, and the definition of a suitable design space.
- For optimization problems in imaging optics, we typically encounter local minima that are sub-optimal. The challenge is to either design optimization algorithms with a higher chance to find the global solution or to define problems that avoid this situation, e.g. by using a convex counterpart.
- Depending on the underlying model, it can be computationally too expensive to use heuristic approaches that need a lot of function evaluations. Thus, different approaches in this context need to be analyzed and developed. We specifically could focus on hybrid constraint methods for multi-objective optimization (e.g. [3]) and multi-objective gradient descent strategies (e.g. [2, 1, 4]).
- For future integration in optical design software, algorithms for multi-objective optimization should be easily accessible, robust and efficient.

Project plan

We envision the following project plan subdivided into work packages (WPs) with a tentative timeline from M1 (month 1) to M60 (month 60):

WP 1: Problem Formulation (M1-M7) This work package deals with the formulation of the multi-objective optimization problem.

T1.1 Existing literature for imaging optics and multi-objective optimization is reviewed.

T1.2 A representative problem from imaging optics is defined to be the subject of research.

T1.3 Objective functions, constraints, and parameter space are defined. (**Milestone 1: Definition of multi-objective problem finished; end of learning phase**)

WP 2: First Optimization Procedure (M8-M16) In this work package the problem is analyzed and a first optimization procedure based on an existing strategy is set up.

T2.1 Implementation and preparation of underlying model.

T2.2 Implementation and execution of given conventional optimization procedure (e.g. heuristic or weighted sum method). (**Milestone 2: First version of optimization pipeline implemented**)

T1.3 Analysis of the problem and the performance of the optimization method in accordance with requirements for optical designs.

T1.4 Report/publication/presentation of results. (**Deliverable 1**)

WP 3: Development of Optimization Strategy (M17-M36) In this work package an improved, problem-specific optimization strategy is developed.

T3.1 Study of shortcoming of existing multi-objective optimization strategies for imaging optics.

T3.2 Algorithmic developments for dealing with local extrema (e.g. through hybridization in a multi-objective context).

T3.3 Considerations for defining (gradient-descent) directions in objective space and their inclusion in existing algorithms. (**Milestone 3: Development of optimization algorithm finalized**)

T3.4 Analysis of algorithmic performance.

T3.5 Publication/Presentation of results. (**Deliverable 2**)

WP 4: Extensions and Further Considerations (M37-M51) In this work package the methodology is refined and applied to another example.

T4.1 Application to at least one additional problem from imaging optics and analysis of generalization

T4.2 Extension of algorithm under consideration of T3.4, definition of future research

T4.3 Considerations concerning efficiency and robustness of the algorithm

T4.4 Code documentation and accessibility features. (**Milestone 4: Research phase finished**)

T4.5 Report/publication of new results.

WP5: Thesis and defense (M52-M60)

T5.1 Thesis writing.

T5.2 Final revision of thesis. (**Deliverable 3**)

T5.3 Preparation of defense, defense ceremony (**Deliverable 4**).

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