In Situ Enhancement of Heliostat Calibration Using Differentiable Ray Tracing and Artificial Intelligence

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1. Introduction

The performance and levelized cost of energy of a solar tower power plant are directly linked to the functionality of its mirrors (heliostats). The better the heliostats can redirect the sun to one surface (receiver), the more power can be generated. In contrast, incorrect alignment not only results in lower energy output, but can cause temperature spikes or gradients and compromise the longevity of the components. The most frequently used calibration method, to correct the heliostat specific errors at commercial power plants is the camera-target method. In this method, a single focal spot is moved from the receiver to a white target below. From the difference between the aimed and the actual aiming points of the focal spot, the errors of the heliostat, e.g. within a geometry model, can be determined by means of mathematical regression. The method is used because it can be fully automated, reliable and quite accurate for a certain period of time after the measurement. There are many other heliostat calibration methods [1] but any new method must measure up to this standard procedure. An improvement of Camera-Target method raises the benchmark for all other methods. The biggest weakness of the method is the time needed per measurement. With about 60 seconds per measurement the data set of a single heliostat rarely grows by more than a few data points per year. The measurement should also not be done frequently, as the process itself decreases the power on the receiver. In order to describe the heliostat completely with all possible errors (rotation, distortion, displacement, partly with angle and time dependencies) it needs many degrees of freedom in the regression and for this the data situation is not sufficient. Thus, the accuracy is not feasible for distant heliostats or modern aimpoint control strategies. This work proposes an in-situ improvement of classical regression using differentiable ray tracings. By means of this AI method, the images of the calibration process can be directly processed. For each measurement, besides the focal spots centroid of area also information about the inclination and orientation of the mirror surface is available, which considerably extends the information content of each measurement. At the same time, the differentiable ray tracing allows a physics-regulated optimization, which provides better gradients than common methods. This not only reduces the number of measurements required, it also allows optimization of previously neglected parameters such as canting, focusing, etc.

2. Method

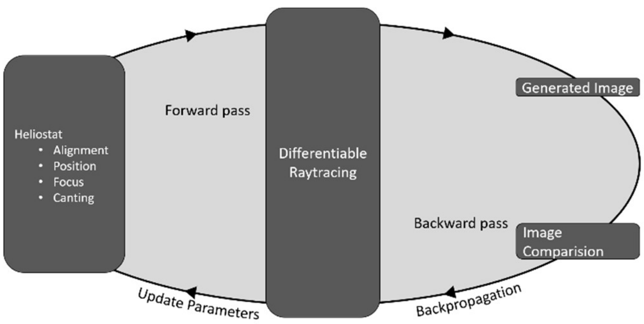

Fig. 1: Optimization workflow for heliostat calibration using diff. ray tracing. The update routine strongly resembles that of neural networks, which is only made possible by the differentiable description of the power plant.

The calibration by means of differentiable ray tracing starts in a simulation environment which describes the situation at the power plant very accurately but with ideal components. This includes the position of the sun at the time of measurement, the geometric shape of the heliostat (described by discrete points or a CAD model) its position, as well es the position, size and orientation of the receiver. The solar rays are now emanated from the sun, reflected at the heliostat and if they reach the receiver, linearly assigned to the neighboring pixels via a binning function.

The incoming irradiance at the receiver is calculated by a Monte-Carlo Integration over all rays:

$$E\left(\vec{x}_{ij}\right) = \sum_{\text{rays}\,k} \sum_{\text{pos}\,l} w_{ijk} \frac{1}{|t_l|^2} \rho(M_l \vec{t}_l) L_e \left(M_l \vec{t}_l\right) \vec{n}_T \cdot \vec{t}_l$$

Where E is the Irradiance, x_{ij} the observed pixel, ρ the bidirectional reflectance distribution, t is the vector between the pixel x_{ij} and and the heliostat position l, L_e the emitted radiance of the Sun, M the reflection Matrix, n_T the normal vector of the receiver and w_{ij}

$$w_{ij} = \sum_{\text{rays}\,k} \sum_{0<n<N} \left(1 - \left(\frac{\vec{x}_k - \vec{x}_n}{\sum(\vec{x}_k - \vec{x}_n)}\right)\right) \delta(x_n - x_{ij})$$

the binning function. This notation allows the entire ray tracing process at the solar tower to be considered fully differentiable for the very first time and thus to be integrated into common AI routines (cf. Fig. 1). The training is further improved by additional intelligent selected loss functions. For example, the choice of start parameters can be completely omitted by punishing the distance of the missed rays to the receiver. Also, unrealistic (large) error parameters can be punished more severely.

3. Results

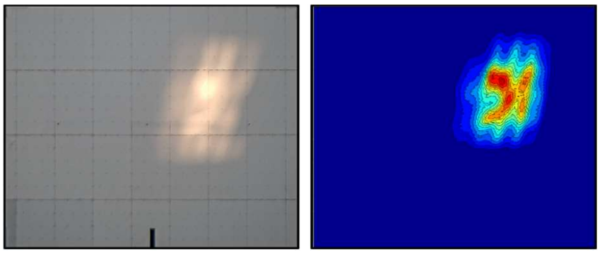

Fig. 2 Real measurement and fitted Raytracing result

In first simulations, heliostats with different rotation errors were created and target images were generated with these. Then an ideal heliostat was initialized and optimized with these images within the AI pipeline. The individual rotation errors could be reconstructed within a few microrads. The method also works natively on real data and remains stable for this purpose (see Fig. 2). All this starting from the very first measurement.

3. Outlook

Differentiable ray tracing opens up completely new possibilities for the heliostat field. Not only can the required data set be significantly reduced by, but also for the first time, variables such as the focal length can be optimized by processing the calibration images directly. The biggest advantage, however, is the possibility to integrate neural networks directly into the ray tracing process, which can gradually compensate the inadequacies of the geometry models used. The entire Code will be published on GitHub.

References

[1] J.C.Sattler et al., (2020). Review of heliostat calibration and tracking control methods.