Performance Increase of Solar Power Plants by applying Deep Learning Algorithms for Heliostatfield Calibration

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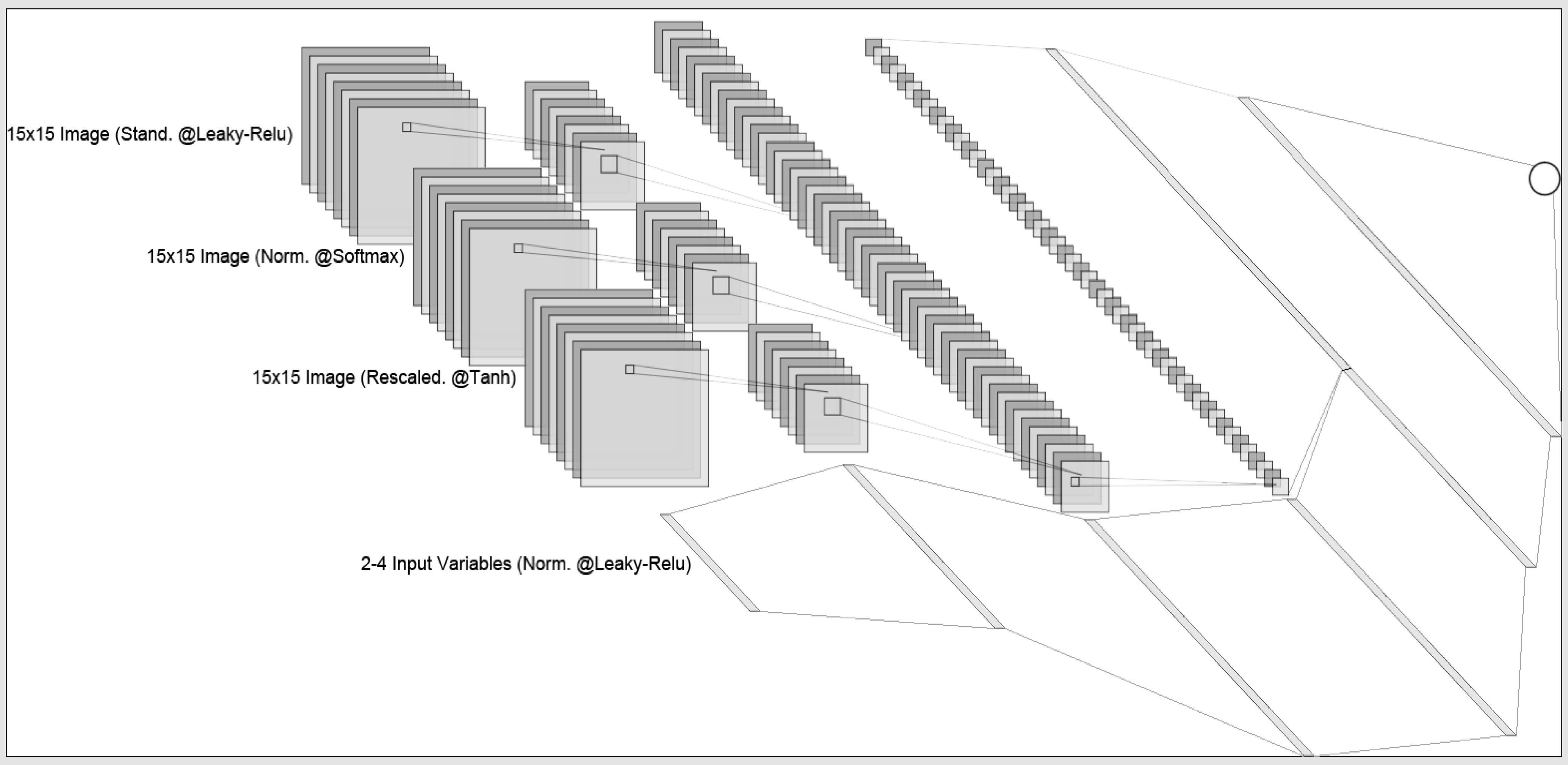


Pic 3: Network with two co-working parts. The first is a convolutional network featuring 3 different activations functions. To all parts the same picture, but with a different augmentation is passed through. The second takes the same inputs as shown in picture 2. Both parts are merged in the last layers. To reduce the complexity of the Problem the network has only one output. The shown structure is only a sketch to present the idea.

Introduction

The efficiency of a solar tower power plant depends directly on the quality of the heliostat alignment. Because heliostats are real objects, they are also erroneous. Its not possible to quantify all of these errors because tracking them is too expensive or not even possible (e.g. pylon inclination, production tolerances etc.)

The errors must be corrected to guarantee a high electricity generation on the one hand and no damage from overheating components on the other hand.

In general we are searching for a mapping function which maps the *real*-position to the desired-position of the heliostat. State of the art in power plants is a regression based calibration method using a kinematic model of the heliostat.

During the calibration procedure the heliostat beam moves from the receiver on a defined point of a measurement target, e.g. the center. A camera can detect the deviation between *real* and *desired* beam position. This procedure is repeated for several sun positions. The deviations are then used in the regression process to adapt fitting parameters for the mapping function.

The outlined state of the art procedure has the following drawbacks:

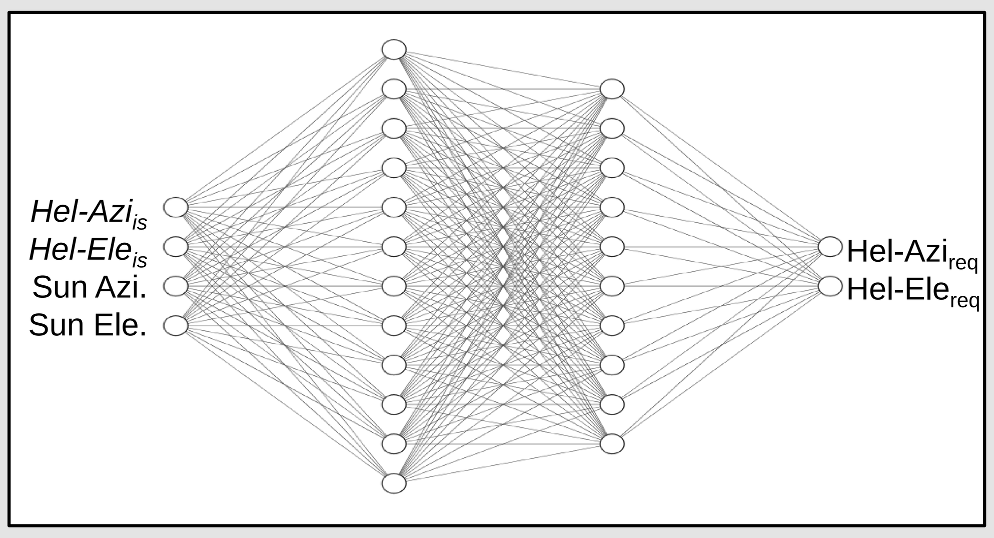
- correlation impossible if geometric parameters are linear dependent
- non-linear errors are neglected by kinematic models
- limitations implied by the default of a function template

The approach of this work is to use a neural network (NN) to overcome the disadvantages of the state of the art regression method.

The ability of NNs to improve model behavior continuously by increasing the amount of data and to fit even most complex functions overcomes the regular parameter driven regression methods in many ways.

So, even if critical errors are not measured properly, the algorithm is able to refocus the heliostat correctly.

NNs are also not limited by the number of parameters.



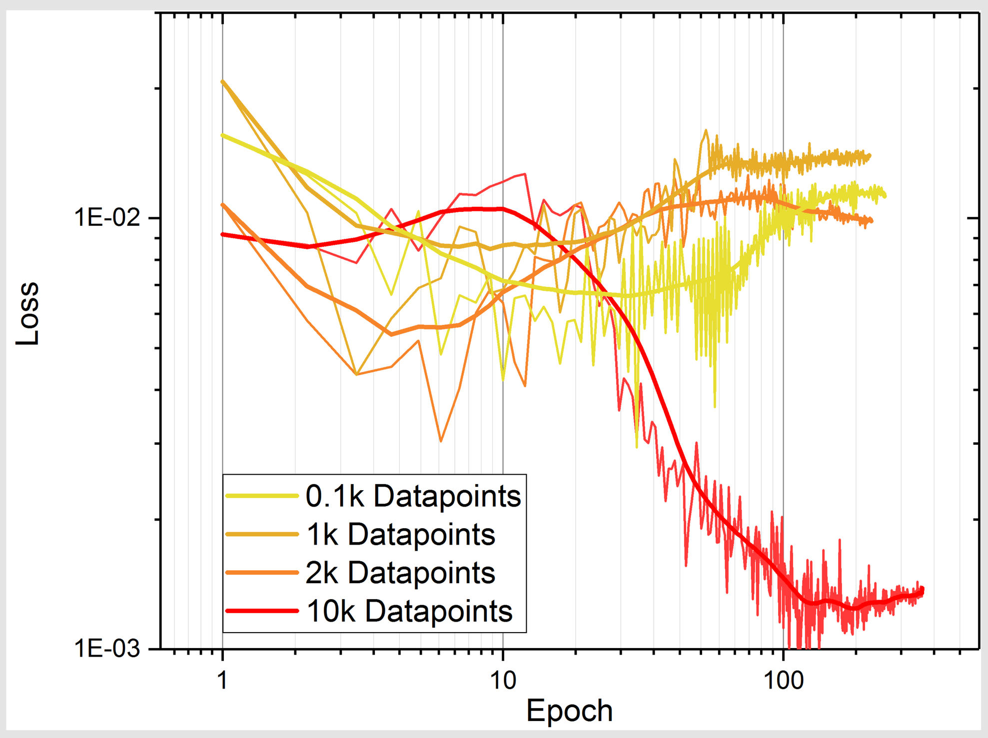
Pic 1: With only two hidden layers Neural Networks are universal function approximators . In our case they are mapping functions from the *is*-position of the heliostat (and the sun position) to the *required*-Heliostat position. With enough Data no other input is needed.

The Method

When applying the AI as the calibrations method, the entire geometry model is replaced by the neural network. However, the actual calibration process is not affected; the calculation of physical parameters becomes obsolete. Instead, the entire network acts as a mapping function between *real* and *desired* position.

To investigate the behavior of the network for data sets of different sizes, we simulated target images using a raytracer and extracted the corresponding heliostat alignments.

For a large Dataset (see picture 2) we can reach an accuracy down to sub arc second range



Pic 2: Comparison between different Dataset sizes, generated by a Raytracer (STRAL). For small Datasets the Network starts to over fit. Best result is below 1 arc second

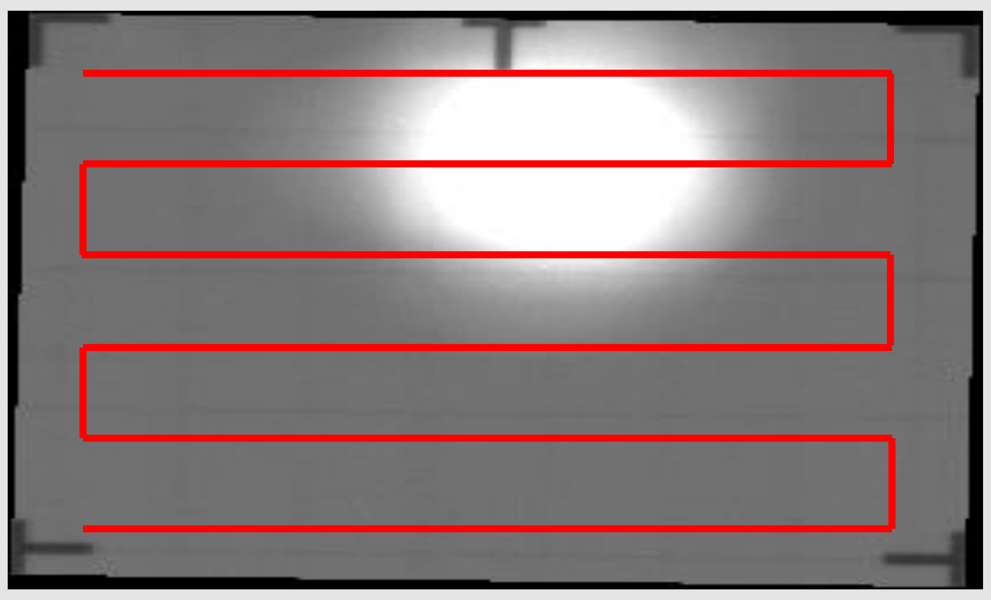
Unfortunately this amount of data is not given in the calibration process, because it would take to much time to gather enough data for each heliostat, also the power plant looses energy every time a heliostat is calibrated. To keep the entire electricity generation cost low, it is necessary to remove the heliostat focal point as seldom as possible.

So we started to feed not only position data through the Network, but also the image data from the target, to get more information out of the existing data. With this method and through an augmentation (see picture 3) of the images in different ways we have succeeded in reducing the required number of images to less than 600 while maintaining high accuracy, also with real measurement data from the Solar Tower Jülich

Conclusion

With the right amount of calibration data a neural network with only 4 inputs to map the *real*- to the *desired*-position is conceivable and the drawbacks of the state of the art method can be overcome. There is also no need of complicated heliostat specific measurements.

We also have shown, that it is possible to reduce the amount of required data by a tenth by passing also image data through the network. The drawback of this technique is that the calibration images which are needed are not available in operation. The solution for this problem is data imputation. Right now we are working on a promising AI driven algorithm to compensate the missing data.



Pic 4: Movement of the Heliostat focal point over the target. The "Neander"-walk would cover the whole Target and will output more Data per calibration. Also a random-walk is conceivable

The lack of data from the regular calibration methods can be circumvented by changing the calibration process from taking single data points and pictures per measurement to tracking full heliostat movement while moving over the Target (see picture 4)

Over the next few months we will test our new approach with the old as well as the new video driven calibration process to obtain more learning data at the Solar Tower Jülich.

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