Smart Heliostat Tracking System based on Artificial Intelligence

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1. Introduction

Central tower solar technology has great potential for cost reduction, which makes it particularly attractive for current and future generation of commercial solar thermal power plants, and even for supplying industrial process heat at high temperatures (above 600°C). The heliostat field is estimated to be responsible for 30% to 60% of the total cost of a solar tower power plant [1,2]. Thus, reducing the cost of the heliostat and its deployment on the solar field, as well as increasing the optical efficiency by correctly measuring the optical performance of the heliostat field, could drastically reduce the overall cost of a plant. Some of the areas with potential for improvement in heliostat cost reduction include the following:

- Current industrial heliostats operate following open-loop tracking strategies with error models. This requires intensive-labour installation procedures and expensive hardware to reliably track the control signals, as there is no feedback for error correction.
- The reflected solar radiation that is not incident on the receiver, known as spillage, highly influences the overall performance of the solar plant. More accurate tracking methods, which reduce or eliminate the calibration time, would decrease the spillage and thus increase plant performance.
- Advanced aiming strategies, which maintain a uniform temperature distribution in the receiver, help to reduce receiver thermal stress and extend its lifetime.

Within the HELIOSUN project, funded by the Spanish Ministerio de Ciencia e Innovación, CIEMAT-Plataforma Solar de Almería (CIEMAT-PSA) is developing a concept called smart heliostat, which arises from applying artificial intelligence and computer vision techniques to traditional heliostats, mainly the machine learning technique called object detection, in order to increase efficiency and reduce costs.

2. Smart Heliostat Tracking System Implementation

The smart heliostat concept developed by CIEMAT-PSA consists of replacing the local control and positioning sensors of the heliostats with a low-cost embedded processor together with a low-cost artificial vision camera. This assembly is installed close to the heliostat's optical axis so that it can move in conjunction with the heliostat's daily tracking movement (Figure 1).

The images captured periodically by the camera installed on the heliostats are sent to a cluster (1 node 4GPUs) of Extremadura Research Centre for Advanced Technologies (CETA-CIEMAT), where an artificial vision algorithm based on the Python OpenCV and Tensorflow packages has been developed. This algorithm allows training the system to automatically identify objects: in particular, the solar receiver and the Sun, but not only these, it also identifies clouds, other heliostats in the surroundings, etc. (Figure 1). Once the positions of the Sun and the receiver in the image captured by the camera are known, thanks to the artificial intelligence detection, it is possible to orient the heliostat so that it reflects and concentrates the solar radiation at a predefined point on the receiver [3].

Fig. 1. Camera and embedded processor installed on a CESA I heliostat at PSA (left), and example of object recognition in recorded images (right).

Five assemblies of this embedded smart tracking system have been installed in five heliostats of the CESA I tower system at the PSA, together with the existing sun-tracking system (local control with solar positioning algorithm and angular encoder sensors) (Figure 1). This parallel installation allows to directly compare tracking performance between both tracking systems to evaluate final performance of the new development. These five operational test units are capturing images periodically, with almost one year of data currently available, which is already a sufficiently large image database for the proper training of object recognition, with almost 100% of recognition of, in particular, the Sun and the target, in a wide range of environmental conditions, being achieved at this time. At this stage of the project, with 5 operational units and plans to install up to 20 within the project, the cost of the new proposed hardware (embedded processor + camera) remains below 80€/unit, with good projections for commercial solar fields with thousands of units.

Next step is the evaluation of the tracking performance of the five smart heliostats, both by direct comparison with the already installed tracking units, and by measuring the reflected spot of each heliostat in the target with a digital camera.

Finally, in parallel to these tasks, and taking advantage of Artificial Intelligence and Deep Learning, an agent is being trained for the automatic distribution of aiming points on the receiver surface, capable of complying both with the total incident power and maximum local power limits on the receiver surface, and to reproduce the predefined flux distribution target over the entire receiver surface.

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