Deep-learning applications to the multi-objective optimisation of IACT array layouts

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Abstract

The relative disposition of individual telescopes in the ground is one of the important factors in optimising the performance of a stereoscopic array of imaging atmospheric Cherenkov telescopes (IACTs). Following previous attempts at an automated survey of the broad parameter space involved using evolutionary algorithms, in this paper we will present a novel approach to optimising the array geometry based on deep learning techniques. The focus of this initial work will be to test the algorithmic approach and will be based on a simplified toy model of the array. Despite being simplified, the model heuristics aims to capture the principal array performance features relevant for the layout optimisation. Our final goal is to create an algorithm capable of scanning the large parameter space involved in the design of a large stereoscopic array of IACTs to assist optimisation of the array geometry (in face of external constraints and multiple performance objectives). The use of simple heuristics precludes direct comparison to existing real-world experiments, but the analysis is internally consistent and gives insight as to the potential of the technique. Deep learning techniques are being increasingly applied to tackle a number of problems in the field of Gamma-ray Astronomy, and this work represents a novel, original application of this modern computational technique to the field

Introduction and Methodology

- Optimisation of an array of IACTs (Imaging Atmospheric Cherenkov Telescopes) means increasing the event detection rate and improve the quality of reconstruction of the primary particle.
- This optimisation is a challenging task, usually done with Monte Carlo and shower simulations.
- Small arrays use regular, symmetric configurations. For larger arrays, the problem is more challenging due to the complexity of the parameter space.
- We use a heuristic model of the array, circumventing the need for extensive shower simulations. We are concerned only in optimising the geometry of the array, not any single telescope.
- Deep Reinforcement Learning is a powerful tool that has been used in several different applications, such as autonomous driving, robotics, gaming, control systems, finances, natural language processing
- The optimisation of an IACT array can be approached in a Reinforcement Learning framework, in which the game is to move the telescopes in ways that the metrics of interested are optimised.
- This initial approach will focus on just a few simple metrics; in the future, we will extend our approach to include more metrics and use shower simulations instead of a simplified heuristic model.

Deep Reinforcement Learning

Reinforcement Learning (RL) refers to algorithms that are trained to achieve a goal or to maximise its rewards. In an RL training there is an agent which performs actions in an environment, receiving a reward for each action. Figure 1 shows the scheme of Reinforcement Learning: an agent interacts with an environment, performing actions at each time step t, which lead to a reward r and a new state of the environment s. Deep Reinforcement Learning combines this framework with Deep Neural Networks as agents, which can be used to tackle complex problems. The main goal is, from a given state, i.e., action and environment, to maximize the reward. For an optimization problem, the maximum score would represent taking actions to maximize some quality factors.

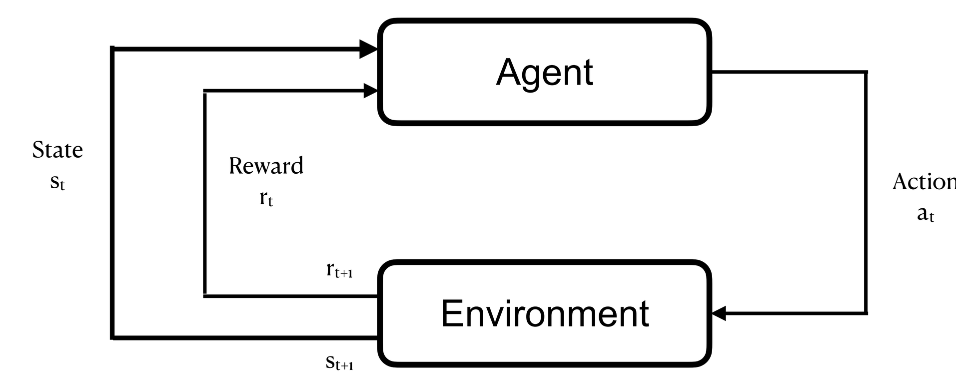

Figure 1:Reinforcement Learning scheme.

Effective Area

The area of detection for an array takes into account the probability of detection of a shower by each telescope and the *multiplicity*, the minimum number of telescopes detecting any given shower. The larger this area, more events will be detected by the telescope; however, increasing the distance between telescopes will decrease the quality of reconstruction, so a balance must be achieved. We use a simplified effective area calculation that is less computationally intense than the full expression, but with very similar results. Figure 3 shows two examples of the probability detection grid for regular arrangements of telescopes and a shower of 1 TeV. This is the metric we try to optimise.

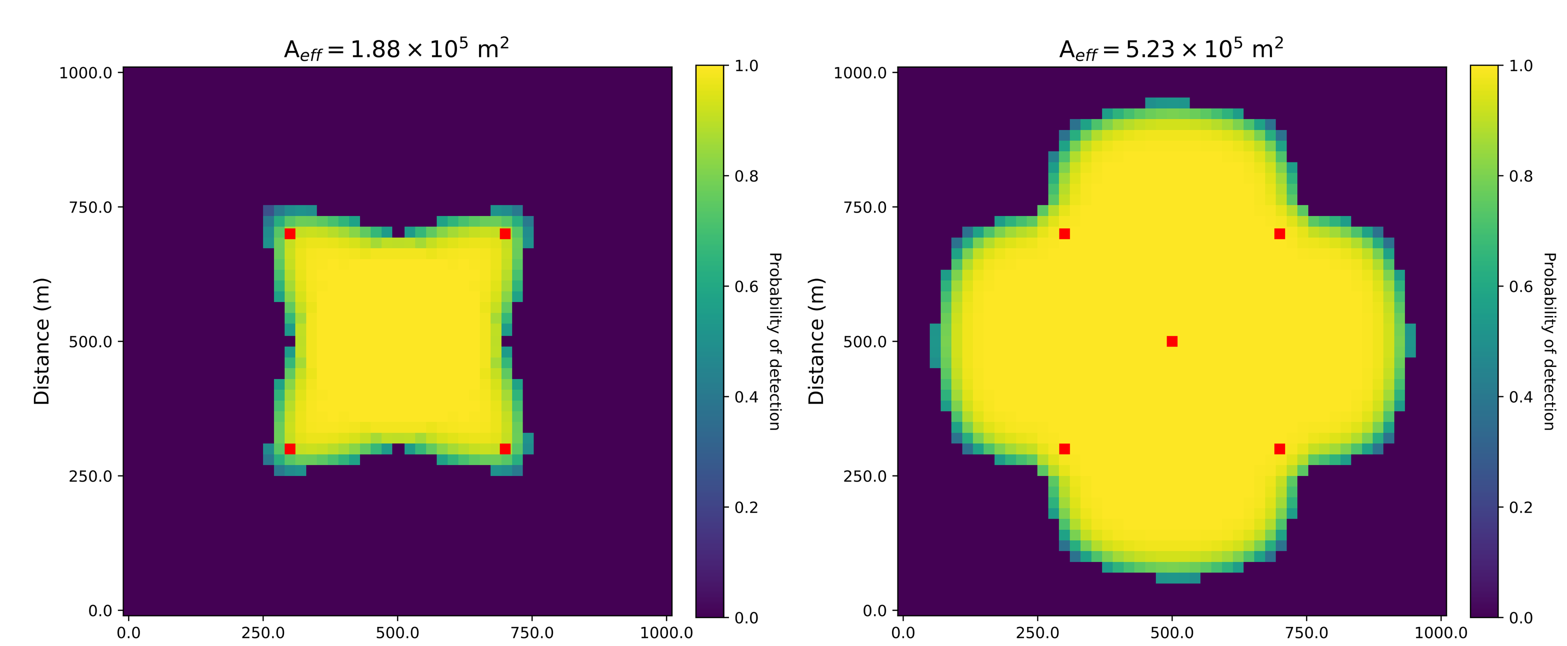

Figure 2:Examples of regular array arrangements with four and five telescopes with their effective areas, both using a multiplicity of three.

Results

We used a square grid with 20 cells on each size, each cell a square with 50 meters side length, with the telescopes starting at random positions. We use the effective and the internal area of the arrangement as features to decide the reward given to the agent. At every time step, the agent can move any telescope to any position, receiving a reward equal depending on the areas before and after the move. If a move leads to a decrease in effective area, the episode is ended and the telescopes return to their initial positions.

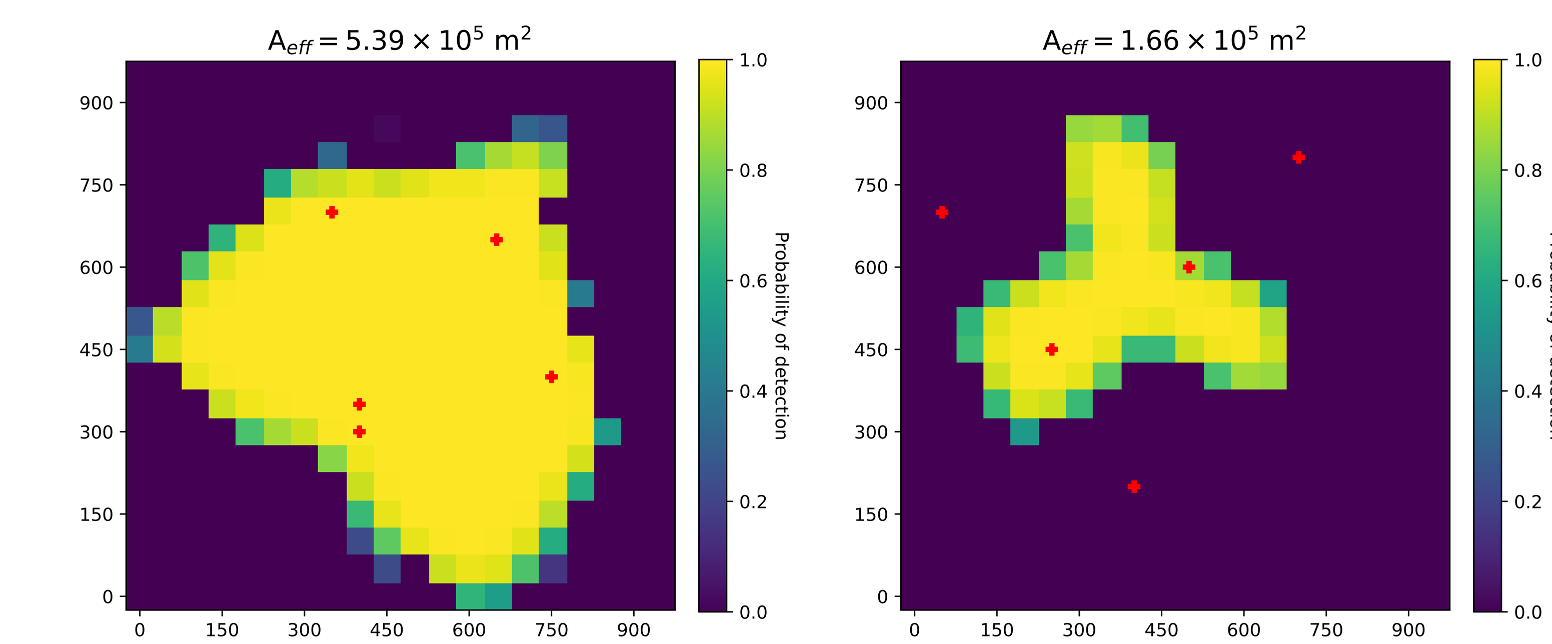

Figure 3:Examples of regular array arrangements with five telescopes with their effective areas. Left: Multiplicity 3. Right: Multiplicity four.

Some examples of configurations reached by the agent are shown above. For lower multiplicity, some telescopes are always close together, since this would take care of the multiplicity without decreasing the effective area too much. When the multiplicity increases, this behaviour is not effective anymore and the agent tends to separate the telescopes.

Future Work

- This is an initial work, using simplified models and concerned only with a few metrics of interest.
- Increase the number of telescopes and include different kinds.
- Optimise for different metrics, including e.g. angular resolution and energy resolution.
- Improve the RL algorithm.
- Use full shower simulation for more realistic results.

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