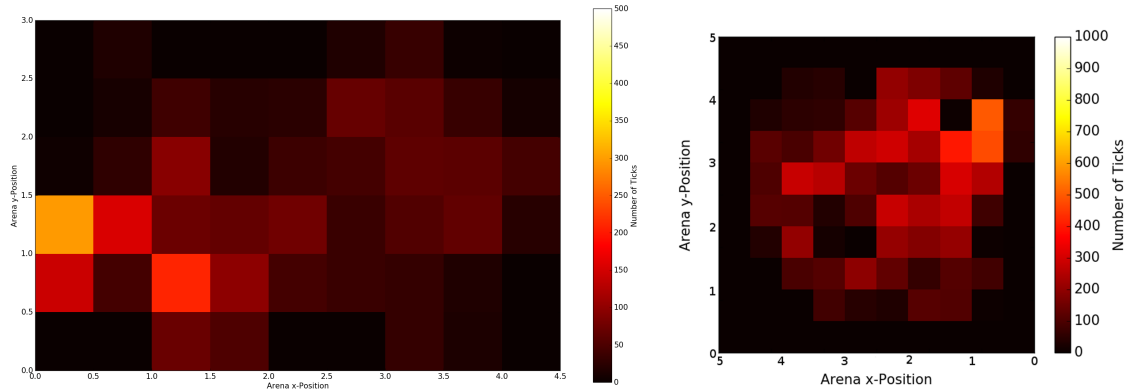


Figure 1: Heatmaps showing the number of ticks that each *cell* was occupied. *Left:* This heat map represents 2 real Crazyflies performing coverage over a 4.5m by 3m sized arena for 120 seconds. *Right:* This heat map represents a 3 agent run in a 5m by 5m sized simulated arena for 300 seconds.



speeds' which are then mapped down to speeds in the x and y directions.

The Crazyfly models were evaluated in a 5m by 5m square arena each containing 3 agents (with a copy of the same network) for 300 simulated seconds. This arena was split into 100 *cells* (0.5m by 0.5m each) which were used as a measurement tool to evaluate how well coverage was achieved. Each agent was placed near the centre such that all the agents started out in a circle; each agent was initiated with a random orientation for each evolutionary run. Each network is evaluated 5 times and the lowest score of those 5 trials is taken as the fitness for that organism. The GA is ran for 50 generations and after that time the best performing individual over all of the generations is reevaluated and observed. A mutation rate of 10%, a population size of 100 and a mutation power of 1.8 were used for NEAT hyperparameters (a full list of parameters are available on request). The fitness function designed for area monitoring in [6] was used in order reward behaviour that lead to *each* cell being visited frequently.

In order to evolve a controller for use on the real Crazyflies, the arena size used during evolution was reduced to 4.5m by 3m (the size of the arena in the lab) and the amount of time in simulation was reduced from 300 seconds to 120 due to the limited battery life on the Crazyflies. The real robotic platform used in the experiments is the Crazyfly 2.0. The quadcopter controller is imported from the best performing individual from 50 generations of the NEAT GA. The distance to the closest Crazyfly is retrieved from the UWB chip and the distance to the closest wall is calculated using the current pose of the Crazyfly provided by a motion capture system.

3 RESULTS & CONCLUSIONS

NEAT successfully evolved coverage behaviour on 3 drones that avoided crashes in all 5 tests. The controller was tested with 3 drones in an arena size of 5m by 5m. Figure 1 (*Right*) is a heat map representing one of these runs where each cell has a value which represents the number of ticks that the cell is occupied. This simulation was ran for 300 seconds at a rate of 10 ticks per second. It is apparent from this image that the drones performed well at

coverage given that there is a relatively similar shade of red across most of the map. This implies that most of the cells were occupied during the run and that they were all occupied for a similar amount of time. 90% of the cells have been visited for at least 1 tick (this is not including the outer border of cells as the agents often avoid this area in order to not crash into the walls) for this run. In order to evaluate the average performance of the individual, the controller was tested for 1000 runs with the same metric as above being taken for each run and averaged over all the performances. This results in a sample mean of: 76.9% and a sample standard deviation of: 10.0%.

In order to demonstrate the *scalability* of the solution, the same controller was evaluated using 6 drones in a 7m by 7m arena. Evaluating the same controller that was evolved on the 5m by 5m arena leads to a sample mean of: 77.2% and a sample standard deviation of: 7.0% of the cells being visited at least once. Finally, to test the *robustness* of the solution with respect to individual failure, the experiment was repeated with 5 drones on an arena size of 7m by 7m in order to simulate the loss of one agent. This experiment resulted in a sample mean of: 73.8% and a sample standard deviation of: 7.3% over 1000 runs. A video showing an individual run and respective heat map of all these experiments is available at: <https://www.youtube.com/watch?v=ifTKCkG98Z0>

The best controller from 50 generations of the more realistic simulation was transferred to the real Crazyfly and then tested for a singular run whilst recording the performance in the form of a heat map - the recorded heat map is shown in Figure 1 (*Left*). The real Crazyflies performed coverage very well, according to the metric used so far, 100% coverage was achieved. Moreover, a very even spread of coverage was achieved leading to a similar shade of red across the entire map. A video of the realistic simulation and the real Crazyfly experiment can be found at:

https://www.youtube.com/watch?v=sEs6doz_LYM&t=7s

To conclude, this paper introduces a method to evolve a neural controller that performs dynamic coverage in simulation and then transfers this optimised controller to a real swarm of MAVs. In contrast to previous works, the system was fully decentralised and had no reliance on GPS. In future work, we will consider using Optical Flow techniques [4, 5, 8] to detect objects in the environment.

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