Here are the results for the test with a low intelligence during 500 episodes:

And then we can see the results with a high intelligence during the same number of episodes:

These results clearly show that our IA has the capacity to learn and to use this knowledge to improve itself.

Here are the results for the test with a low exploration during 500 episodes:

And then we can see the results with a high exploration during the same number of episodes:

We can now see that when we need to find many people, for example in situations involving bombs or earthquakes, we set the exploration level high. On the other hand, when we need to find a single person, such as in cases of avalanches or missing persons, we set the exploration level low

With the improvement of this AI, compared to a helicopter, the cost of operation will decrease and be more efficient.

For example, the cost of a mission using a helicopter in Europe is nearly 2 500-3 500 €/hour compared to a drone that is about 300-400 €/hour. This means that using a drone is about eight times cheaper than using helicopters. For one mission we can deploy eight drones instead of one single helicopter.

Therefore, in real-life applications, we integrate this code into our drone and equip it with infrared sensors. Once the drone detects a person, it sends a signal that allows emergency services to quickly locate and assist injured or trapped people.

Conclusion

Because of limited time and resources, we mainly developed a program able to detect bodies using a basic computer vision algorithm. This is an important first step, since finding victims quickly is essential in any SAR (Search And Rescue) mission. However, this remains far from the complete and fully autonomous system we originally imagined.

With more time, better equipments, and stronger technical skills, many improvements could have been added like:

- A real autonomous navigation system, using a fully trained RL model capable of avoiding obstacles and adapting to changing environments.
- Betters sensors, like IR, ultrasonic sensors, or more efficient thermal cameras, to give the drone a more accurate view of its surroundings, even in dark or smoky areas.
- A physical prototype, allowing us to test the drone in real conditions instead of only in simulations.
- A communication system that works without GPS, so the drone could operate even when networks are damaged or unavailable.
- A more advanced vision model, able to detect not only bodies but also movement, distress gestures, or vital signs using thermal images.

Application in Real-Life Conditions

In real-life missions, this detection code could be integrated into a fast and lightweight rescue drone equipped with different sensors. The camera would provide visual data for body detection, while infrared sensors or thermal cameras would help identify heat signatures, even in darkness or through smoke. The drone's onboard computer would run the detection program in real time, allowing it to immediately find potential survivors. Combined with a reinforced program, powerful motors, and obstacle-avoidance sensors, the drone could rapidly go into collapsed buildings or dangerous areas where human rescuers can't go. This shows how our basic detection algorithm can become a practical and life-saving tool when installed on a real, fully equipped rescue drone.

Evolution Through Reinforcement Learning

To evaluate how the drone improves with Reinforcement Learning, we can track its performance across many training episodes. For example, we can measure the number of successful flights, the number of obstacles avoided, or the time needed to find a target. As training continues, the drone becomes more efficient and makes fewer mistakes.

This were the results that we expected from our code:

Number of Training Episodes	Success Rate	Average Crashes	Average Time to Target
10	35%	High	Very slow
100	48%	High	Slow
250	62%	Medium	Moderate
500	78%	Low	Faster
1000	96%	Very low	Very fast

And here are the real results that we got from our own tests:

If we raise these results on a simple learning curve, we would see a rapid improvement at the beginning (between 10 and 100 episodes), followed by more stable and optimized behaviour as the RL model reaches 1000 episodes. This progression clearly shows how the drone "learns" from its mistakes and gradually becomes safer, faster, and more efficient thanks to Reinforcement Learning.

In conclusion, SOLDADOSS represents a solid starting point for future rescue technologies. Although our current version only performs simple visual detection, it shows the potential of AI for improving safety and efficiency in disaster response. With more time, resources, and development, this project could grow into a powerful and fully autonomous system capable of saving lives in critical situations.