The work described in this thesis was inspired by a vision of truly autonomous robots that can adapt their behaviour, possibly even their shape, to suit varying tasks and circumstances. Autonomy occurs at two levels: not only do the robots perform their tasks without external control, they also adapt their behaviour without referral to external oversight and so learn autonomously.

Such versatility is well beyond most autonomous robots that have been designed for particular tasks (“weld the body to the chassis”) in well-defined environments. To be able to handle unexpected circumstances and tasks, robots must acquire the ability to learn appropriate behaviours and morphologies as they encounter these circumstances and are given these tasks. This ability to learn, to adapt, autonomously is the focus of our research.

Robots can be programmed to adapt individually, by themselves, without referral to any external overseers, but when there are multiple robots that try to tackle the same task it makes sense to seek strength in numbers by learning collectively. Robots can then combine their knowledge through evolution (evolutionary adaptation) or they can exchange knowledge through social interaction (social learning) to boost their individual learning processes. Thus, there are three possible ways in
which a collective of robots can implement adaptivity: individually, socially and evolutionarily.

The research described in this thesis was undertaken as part of the symbrion project, which envisages groups of dozens of robots that can link together to form and manipulate ‘organisms’, but that can also act separately, in ‘swarm mode’. The robots must be able to learn, jointly as well as individually, to perform tasks in diverse environments: they must exhibit the adaptivity lacking in regular robotics.

We have looked closely at learning behaviour at the individual level. One of our fundamental choices was to rely on evolution as the main enabler of adaptivity. Therefore, we implement even individual learning through an evolutionary algorithm, encapsulating a population of evolving controllers in each individual robot. This may be somewhat confusing, since this mechanism does not implement evolution at the level of the robot collective. This becomes clear when we consider that there is no exchange of information among the robots, and robots learn in isolation just as they learn in the presence of their peers. Adding such exchange of information amounts to introducing ‘proper’ evolution, leading to a distributed evolutionary mechanism. Finally, we can combine these two mechanisms to obtain an implementation of social learning.

We have performed comparative analyses with algorithms that implement evolutionary adaptation by distributing evolution over the robots in the collective and hybrid algorithms that combine encapsulated and distributed evolution into a social learning approach.

We set out to answer three main research questions:

− Can we devise evolutionary algorithms that allow robots to learn to perform simple tasks autonomously?

− Which approach –encapsulated, distributed or hybrid– offers the best results?

− How does the performance of our algorithms depend on parameter settings?

We have developed and tested an encapsulated evolutionary algorithm called \((\mu + 1)\) on-line that provides for individual learning in robots. This algorithm proved capable of adapting robot behaviour to perform a number of simple tasks like obstacle avoidance and patrolling, allowing the robots to learn to perform these tasks without the need for any external oversight.
We have also developed distributed and hybrid alternatives for \((\mu + 1)\) on-line, and we have seen that it is in general beneficial to learn collectively, but that care should be taken when the task implies competition among the robots.

Extensive tests of the algorithms have shown—as expected— that their performance depends profoundly on the parameter settings. However, we found that there is no ‘silver bullet’ setting that works equally well across our experiments. This indicates a need for further research into parameter control schemes that will allow the algorithms to adjust their parameters according to the circumstances and the task.