Chapter 7

Adaptability and Evolvability

All of this work began with the premise that a combination of a computational model of embryogeny and an evolutionary system are behind the emergence of all of the useful characteristics observed in this work. Throughout the course of this work it has become apparent that this is not strictly true. The traits of robustness and scalability seem to be an inherent property of the embryogeny model since their behaviour does not seem to be linked with fitness or to vary during evolution. This chapter further investigates the relationship between simulated evolution and the computational model of embryogeny, particularly focusing on the origins of the apparent bias towards modular structure. The performances of various search techniques are compared and any dependencies of the observed characteristics of robustness, scalability and modularity upon the search process are determined.

Simulating evolution is a process of optimisation and search, whether it be finding optimal parameters for the approximation of some static function or to maintain performance in some dynamic and competitive environment. At the core of any evolutionary algorithm is the means to strive to maintain or improve the fitness of the individuals it operates upon, whether the fitness is some artificially defined function or an inherent feature of the system.

Adaptability refers to the ability of an organism to change its physical structure or
behaviour in order to make it more likely to survive in its environment. As such, the adaptations usually coincide with a change in the organism’s environment. Organisms can adapt to changes in their environment during their lifetimes through learning or phenotypic robustness which is often referred to as \textit{acclimation}. However these adaptations can also occur over a much greater time scale as a result of an evolutionary process.

In this respect the success of simulated evolution is determined by how it adapts an individual in an attempt to improve or maintain its fitness. These adaptations are dependent upon many features of the algorithm such as the genetic representation, selection criteria, search operators and evaluation process.

One option for producing a successful process of adaptations in an evolutionary algorithm is to use domain knowledge of the problem at hand. The characteristics of the evolutionary algorithm can then be selected to suit the problem directly. Of course in this case it would be advisable to consider a much greater range of search algorithms not just those inspired by evolutionary processes. However, using this approach, when little or no domain knowledge is available, leaves us at the mercy of educated guesses and trial and error.

What makes evolutionary algorithms more powerful than simpler search processes, such as hill climbing, is the way in which these adaptations can be directed. If the population is used to full advantage, it stores more than just a set of individuals. Based on how the stored individuals relate to each other, further information can be inferred about the search process itself, such as what combination of alleles are good and bad. This is termed ‘population information’ and is one of the key features that make evolutionary algorithms more successful with difficult and noisy problems.

\textit{Eolvability} refers to the ability of an organism to adapt through evolutionary changes to new or altered environments. It can be measured as the rate at which successful
mutants can be produced from an individual. An individual is considered to be more evolvable when, whilst undergoing search operations, it has a higher rate of producing useful mutants.

7.1 Search Algorithms and Computational Embryogeny

Throughout this work, results have been obtained using a specified evolutionary algorithm\(^1\). A comparison between the evolutionary approach and both a random and local search is made in terms of performance but also to determine if there is a change in the observed capabilities of robustness, scalability and modularity. All results are obtained using the French flag like pattern as a target template.

For random search, each generation of the search algorithm consists of the creation, at random, of a new population of individuals. The only transfer of information from the previous generation is the fittest individual found so far. Figure 7.1 shows performance, on average for 10 runs for 1000 iterations, of the random search algorithm in terms of the fitness of the optimal individual discovered over time. The figure also shows the typical behaviour of both the average fitness and diversity of the randomly generated population of individuals at each iteration of the random search.

A local search is conducted using a hill-climbing algorithm. From the current point of search, a subset of the neighbourhood is generated using single point mutations from the current position. If any neighbouring individual in the generated sample has an improved or equal fitness to the current point of search it becomes the new point of search. Figure 7.2 shows the performance of this local search hill climber in terms of optimal fitness and the average fitness and diversity of the sampled neighbourhood.

To ensure the comparisons between the three search algorithms are as fair as possible,\(^1\)Evolutionary algorithm described in section 3.5.3
Figure 7.1: Fitness and diversity of individuals generated during a random search.

the number of evaluations required at each generation is consistent across each search algorithm. Although this does not ensure that the computational cost of each generation is exactly equal for each search algorithm it does provide accurate enough information to draw useful conclusions.

It is clear, from the results presented in figures 7.1, 7.2 and 7.3, that the evolutionary approach is the most successful, achieving higher levels of up to 90% fitness within 1000 generations as compared to 86% for hill climbing and 79% for random search. This would be expected for such a potentially discontinuous search space introduced by the complex mapping process. The evolutionary approach also shows much greater variance in diversity of the sample (population) upon which the search is based, whilst for both local and random search the diversity of the samples stays much more consistent. The variation of diversity reflects the evolutionary algorithms ability to sustain both localised and more
globalised search, through divergence and convergence of the population, supported by search operators and selection bias.

Figures 7.4, 7.5 and 7.6 show both measures of phenotypic robustness\(^2\) and scalability\(^3\) during the three forms of search. The results show that the robust and scalable behaviours of the phenotype are apparent throughout all three forms of search and at all stages of the search. The relatively low standard deviation of the results also indicates that these robust and scalable behaviours are ubiquitous and widespread, suggesting that the vast majority of, if not all, individuals exhibit high levels of phenotypic robustness and scalability.

Figures 7.7, 7.8 and 7.9 shows the measurement of alignment between genotypic and phenotypic structures \(^4\) during the three forms of search. For each of the three forms of

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\(^2\)The method of measuring phenotypic robustness was discussed in chapter 4, section 4.3
\(^3\)Measuring scalability during evolution was outlined in chapter 5, section 5.2.2
\(^4\)The alignment of genotypic and phenotypic structures is outlined in chapter 6, section 6.5.2
search the alignment is seen to generally increase, although in an extremely noisy fashion, through iterations of the search process.

Each of these measures shows that all three algorithms produce individuals that exhibit capabilities of robustness, scalability and alignment. However, in order to determine whether or not these properties are inherent to the computational model of embryogeny, or are a product of the interaction with an evolutionary system, there would need to be a discernable difference in the trend of robustness, scalability and alignment between the evolutionary process and other forms of search. Whilst figures 7.4 through 7.9 do show clear trends, over a number of iterations for both robustness, scalability and modularity, a distinct differences between the various search processes is much less clear, especially in the case of figures 7.7, 7.8 and 7.9. The disparity in performance in the various search algorithms obscures any real underlying trends. A means of comparison is required that
Figure 7.4: Robustness and scalability of optimal individuals found during random search.

Figure 7.5: Robustness and scalability of optimal individuals found during local hill climbing search.

Figure 7.6: Robustness and scalability of optimal individuals found during evolutionary search.
Figure 7.7: Modularity of optimal individuals found during random search.

Figure 7.8: Modularity of optimal individuals found during local hill climbing search.

Figure 7.9: Modularity of optimal individuals found during evolutionary search.
Figure 7.10: The fitness both before and after damage and repair applied to individuals discovered during search.

is less dependent upon the performance of the search process over time. This can be achieved by measuring these characteristics with respect to fitness rather than iterations. Figure 7.10 outlines trends in robustness by showing the fitness both before and after 50% damage and repair. A similar linear trend can be observed for each of the search process. Figure 7.11 shows the relative fitness of individuals evaluated at 128 and 256 cells. This again shows a clear linear trend, highlighting that each search process is equally capable of finding individuals of similar scalability for any given fitness. Figure 7.12 shows the alignment, between genotypic and phenotypic structures, plotted against the fitness of the individual for all three forms of search. Although not following a linear trend, each of the search algorithms do seem to correspond to the same trend of increasing alignment with fitness.
Figure 7.11: The fitness at two differing scale of individuals discovered during search.

It is clear from these results that, if the performance of the search algorithm is ignored, there is a clear similarity in the trends of robustness, scalability and alignment between the three forms of search. From this it can be established that, for the results presented here, these characteristics are not biased by any one of the three search processes. Therefore, the robust, scalable and modular behaviour of individuals is an inherent property of the embryogeny mapping process and is independent of the search process.

7.2 Is Evolution the Key to the Behaviours Observed in this Work?

The observations made in this chapter suggest that all of the behaviours obtained within this work are likely to be obtained by any search algorithm. However, it has also been
observed that an evolutionary approach certainly seems to have an advantage over the more simplistic hill-climbing local search and random search in the sense that it finds optimal individuals using less computational resources (as seen in figures 7.1, 7.2 and 7.3). A simple argument for this advantage could be made by pointing out the noisy nature of the search landscape to which an evolutionary approach is the better suited of the three search algorithms.

However, there are some interesting observations that can be made about the nature of the alignment between genotypic and phenotypic structures and what this means for a search process. Altenberg’s hypothesis of *Constructional Selection* [4, 3] states:

“Selection during the origin of genes provides a filter on the construction of the genotype-phenotype map that naturally produces evolvability.”

Figure 7.12: Alignment of genotypic and phenotypic structures against their relative fitness.
Altenberg suggests that a search process that incrementally changes the degrees of freedom of a genetic representation will do so to more closely match the degrees of freedom of the phenotypic domain. This is because such individuals are more evolvable, since a change in a variable in such a genotype is more likely to result in some measurable response, in the associated variable, in the phenotype.

Another way of viewing this argument is to say that an evolutionary search process will bias towards individuals that, once mapped from genotypic space to phenotypic space, will form a relatively smooth search landscape that is easier to traverse. The increasing alignment between genotypic and phenotypic structure shown in the results of figure 7.12 are symptomatic of such an alignment of the degrees of freedom.

Therefore, one could argue that an algorithm that utilises iterative adaptations to existing solutions would be more suited to constructing modular structures and thus better suited to navigating the search space embodied by the model of computational embryogeny introduced in this work.

7.3 Summary

This chapter tests the hypothesis that there is an interaction between simulated evolution and a computational model of embryogeny that produces the robust, scalable and modular characteristics that have been observed in the previous chapters.

Three forms of search are compared: a random search, a local hill climber and simulated evolution. Analysis of individuals produced from each of these search algorithms shows that each produces individuals that exhibit characteristics of robustness, scalability and modularity. Furthermore the algorithms follow similar trends for each of these characteristics relative to fitness.

This suggests that these characteristics are not a result of some search bias and therefore not a result of a relationship specifically with simulated evolution. Since
random search produces the same behaviour as local and evolutionary search then the
characteristics observed in this work cannot be a result of an interaction between the
computational model of embryogeny and an iterative adaptive search process.

This result is not unexpected based upon the findings for both robustness and
scalability that showed them to be characteristics that were consistent and ubiquitous even
within a randomly generated population. However, this conclusion, from the perspective
of modularity, is more surprising. A clear trend of increase was observed for the modularity
measures during evolution and strong arguments have been given as to why evolution may
bias such modularity. For the same trend to appear for both local and random search it
is clear that the modularity is simply a consequence of the fitness of an individual such
that fitter individuals tend to result in increased modularity.