Chapter 4

ADAPTATION TO STATIC ENVIRONMENTS

The idea underlying adaptation in biology is pretty simple as it rouses the notion of walking and climbing in a fitness landscape. The evoked image is powerful since it allows us to consider search as a process which only relies on the properties of the particular landscape observed. Thinking in terms of natural landscapes such as peaks, valleys and so on can enhance insight into the difficulty of adaptation, but it can also give rise to new strategies for exploring complex search spaces.

The chapter investigates the capabilities of adaptation for population-based search techniques developed in evolutionary computation. The requirements of successful adaptation are approached from two directions. In the first section we take a close look at the adaptive behavior of GAs. In next section we investigate properties of problem environments in reference to a fitness landscape. In order to gain insight into the potentials of evolutionary search we assume a static environment throughout this chapter, i.e. we consider a fitness landscape as fixed in structure. The notion of a landscape, however, is abstract enough to encompass a dynamic environment as well. This will be investigated later on.

The last section presents the basic principles of evolutionary search in the context of other local search techniques. In combinatorial optimization EAs can be an alternative for algorithms like Simulated Annealing or Tabu Search. Since the landscape model is restricted neither to specific problems nor to the viewpoint of specific methods it provides a framework suitable to access general concepts of local search. By predicting the difficulty of local search with respect to the structure of a fitness landscape we finally attain a cautious assessment of EAs and the scope of problems they are supposed to be applied to.
1. CONVERGENCE IN EVOLUTIONARY ALGORITHMS

The dynamic behavior of EAs must be taken as the most crucial point regarding their performance. As outlined in the previous chapter, the dynamic of evolutionary search mainly depends on the intensity of selection. In order to drive a population of individuals towards promising regions of a search space the gathered information is continuously condensed. If this process stagnates, the algorithm is said to have converged. If a population does not converge, it can hardly adapt to a given fitness function. On the other hand, a converged population cannot yield further adaptation. For this reason convergence and adaptation are closely tied processes and their control is an important need in order to make an algorithm work.

This section is divided into three parts. First we provide a method for measuring the state of convergence in a population of binary strings and then we review recent approaches to control the convergence process. Finally a distributed control model of local recombination is presented which enables the individuals of a population to react flexible on their state of convergence.

1.1 MEASURING CONVERGENCE

Often a particular GA performs well for relatively small optimization problems but it leads to poor results if it is applied to larger instances of the same problem type. In order to achieve a more thorough search we may react by increasing the population size of the GA. But, as mentioned before, there is only little trade-off for using a larger population. The attempt to improve search by enlarging the population at sufficient size is usually computational prohibitive. In natural evolution time is of no concern and adaptation can rely on evolving huge populations. In simulated evolution this is different and therefore research has spent effort to gain more insight into the requirements for adapting towards near-optimal solutions.

As we have learned from population genetics, the average fitness of a finite population tends to stabilize from generation to generation. The reason that the individuals show increasingly similar fitness results from a similarity in terms of their information encoded. In other words, the behavior of GAs provides a dynamic which can result in stagnation at the information processing level which is called convergence. A qualitative description of GA convergence is given as follows: in order to gain further progress, above average fit solutions are selected at high rates for recombination. If these partially adapted strings become similar, the