1. Conclusions

1.1. Summary

The aim of my Master Thesis was to find an effective fitness deterioration algorithm as defined in chapter 4, which minimizes the chance of multiple exploration of the same solution during the course of the *Sequential niching* algorithm. Taking into account the results of tests described in chapter 5 we may come to the conclusion that the goal was reached. However, tests was performed only for simple multimodal problems in which the obtained clusters were convex and provides a lot of information about underlying basins of attraction. Applying the algorithm for more demanding functions should be the next step in the further development of the algorithm.

The assumption that distribution of individuals inside a cluster provides information about its shape oversimplifies the real nature of the evolutionary algorithms, where the population distribution inside basins of attraction is very hard to predict and depends on many factors, including recombination versus mutation rate, selection algorithm, definition of genetic operators such as mutation and crossover. We can expect satisfactory results when choosing proportionate selection and genetic operators which are based on normal distribution. *Fitness Proportionate Selection* usually causes faster convergence to local solutions and normal distribution based reproduction operators tends to produce populations with useful information about fitness landscape.

Choosing weighted crunching functions for *Fitness deterioration* (as described in section 4.3) is always more accurate than the *Basic scheme* described in section 4.2. You can sacrifice accuracy for speed when fitness function evaluation is very costly by using the *Basic scheme*.

The most valuable outcomes of this work are:

– definition and implementation of a hybrid metaheuristic called *Sequential niching* which may be used for solving multimodal optimization problems.

– applying clustering algorithms as a reasonable stop criterion for real-valued evolutionary algorithms

– using properties of *OPTICS ordering* [**?**] to improve the deterioration process

– definition and implementation of two variants of the fitness deterioration algorithm which might be used in different scenarios depending on the expected speed and accuracy of the global optimization

- definition and implementation of the *Covariance Matrix Adaptation* algorithm which improves the efficiency of the fitness deterioration
- creation of an extensible, lightweight framework which implements all of the algorithms and ideas presented in this work and which can be used for further research

1.2. Future Research

This work focuses mainly on the *Fitness Deterioration* algorithm and shows the result of Basic and Weighted variants of the algorithm applied to simple multimodal functions (see chapter 4). Given the *Sequential niching* algorithm described at the beginning of this paper (chapter 2), the main direction of the future research should be to test this algorithm using many different evolutionary algorithms and evolution strategy. The most promising algorithm to choose would be *Hierarchical Genetic Strategy* (HGS) [**?**].

The Hierarchical Genetic Strategy (HGS) performs efficient concurrent search in the optimization landscape by many small populations. The creation of these populations is governed by dependent genetic processes with low complexity [**?**]. HGS is an example of parallel genetic algorithms and it performs very well especially in case of problems with many local extrema. Taking into account the fact that HGS is likely to find many solutions in a single run of the algorithm and that the hierarchy of populations generated by the algorithm are rapidly convergent it would be very efficient from the standpoint of the deterioration process.

There are many aspects of the implementation of *Sequential niching* algorithm, described in chapter 6, which can be improved as well. The framework uses very simple concurrency model which may be further developed to improve the overall performance of the algorithm. The most costly stages of the algorithm include: fitness function computations during EA algorithm and creation of *OPTICS ordering* [**?**]. The former problem might be solved by introducing some of the known parallel genetic algorithms and the latter might be tackled by proper domain decomposition. If we want to introduce a highly concurrent EA model again it would be best to use HGS because of its natural concurrent character.