Application of Hyperheuristics in Dynamic Environments

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Abstract. It has been shown that evolutionary algorithms enriched with heuristics are capable of finding promising solutions for dynamic optimization problems. The utilization of hyperheuristics for the maintenance of cooperation among such heuristics is an interesting topic. In this study, hypermutation, random initialization and using a diploid representation are chosen as the three basic techniques that enable evolutionary algorithms to cope with dynamic environments. Adaptive and self-adaptive hyperheuristics have been integrated in the system to control the progress of the lower level basic techniques. This paper aims to report the results of a series of experiments which were performed to test the performance of adaptive and self-adaptive hyperheuristics for the coordination of the specified basic techniques under different change conditions. The dynamic bit-matching problem is chosen as the test problem.

1. Introduction

An optimization problem with changing optima requires an algorithm that can track the optima as closely as possible. Evolutionary Algorithms (EAs) [1] appear as promising choices, owing to their ability to explore several solutions in parallel, their robustness and their potential for adaptibility. Meanwhile, early convergence, difficulties in parameter tuning and the need for introducing additional diversity for tracking changing optima are the drawbacks of EAs.

A hyperheuristic [2] is a higher level operator that determines which low level heuristic(s) will be applied at each iteration of the search process. Therefore, a hyperheuristic approach can be used to choose a specific dynamic environment handling method whenever a change occurs in the system. This approach may be adaptive or self-adaptive. The adaptive hyperheuristic used in this study examines the overall success of the basic methods and allows more efficient methods to have higher chances of being selected. In the self-adaptivite hyperheuristic, all individuals are allowed to evolve their own weights for each basic technique. The method to be applied on the individual depends on the probabilities determined using the corresponding weights of the individual. Hence, it is expected that more promising methods will have higher weight values on fitter individuals.

The main purpose of this study is to perform a preliminary experimental analysis to compare how the two different hyperheuristic techniques explained above coordinate the progress of the chosen basic dynamic environment handling methods to track shifting optima in a simple test problem (the dynamic bit-matching problem) under varying change conditions.

2. Hyperheuristics for Dynamic Environments

Generally, for a dynamic problem, a solution that is optimal or near optimal at a certain time may lose its quality in the next time steps, or may even become infeasible. The main goal of the optimization algorithm chosen for solving the dynamic problem should be to track the shifting optima through time as closely as possible. Details on handling changing environments can be found in [3,4]. The basic methods used in this study, hypermutation, random initialization and diploidy, are further summarized below.

In [5], Cobb proposed the hypermutation technique, which keeps track of the quality of the best performers over time and increases the mutation rate drastically when this measure worsens. As long as the environment is stationary, the algorithm works like a regular genetic algorithm (GA). When a change is detected, the amount of variation in the population is increased through raising the mutation rate.

In [6], Grefenstette proposed the random immigrants method that replaces a fixed percentage of the population with randomly generated individuals at every generation. In this study, a modified version of this approach is used where some individuals in the population are randomly initialized after a change in the environment.

GAs with a diploid representation have been proven to be successful especially for dynamic environments which oscillate between two states. In the diploid GA, each individual has two chromosomes and a phenotype. In the basic Ng-Wong [7] approach, the chromosomes contain four genotypic alleles two of which are dominant and the other two are recessive. The gene that appears on the phenotype takes the value of the dominant allele. There is no dominance change in this basic version.

In the hyperheuristic approach [2], a high level search operator is applied in an iterative manner to control a set of low level heuristics during the search process. In a dynamic optimization problem, the success of a method is closely related to the nature of the changes. A method such as hypermutation which performs better in an environment where the changes are not severe may become inappropriate during changes of higher severities. In this case, utilization of a hyperheuristic which determines the method to be applied in a specific environment may result in better adaptation for problems with changes of varying severities.

The hyperheuristic for choosing the technique to apply when change occurs, may be adaptive or self-adaptive. The adaptive hyperheuristic used in this study maintains the global success measures for each method. If an individual chooses a method and is successful after a change, the global selection weight of the corresponding method is increased or it is decreased otherwise. Probability of each method being selected for application on an individual is calculated based on its global selection weight. In the self-adaptive hyperheuristic, each individual has a weight array as part of its chromosome which evolves through time along with the individual. These weight values are used to calculate the probability of each method being chosen by the individual.

3. Experiments and Results

This study focuses on how random (one of the techniques is chosen randomly by each individual), adaptive and self-adaptive hyperheuristics organize basic dynamic environment methods for changes with different severities. Since this is a preliminary study to see feasibility of these approaches, only three basic techniques are considered in a limited scenario; the frequency is kept at a constant medium rate and changes are explicitly made known to the system. The dynamic version of the bit-matching problem is chosen as the benchmark and a standard GA that utilizes a binary representation, generational replacement, binary tournament selection, uniform crossover and bit-flip mutation is used.

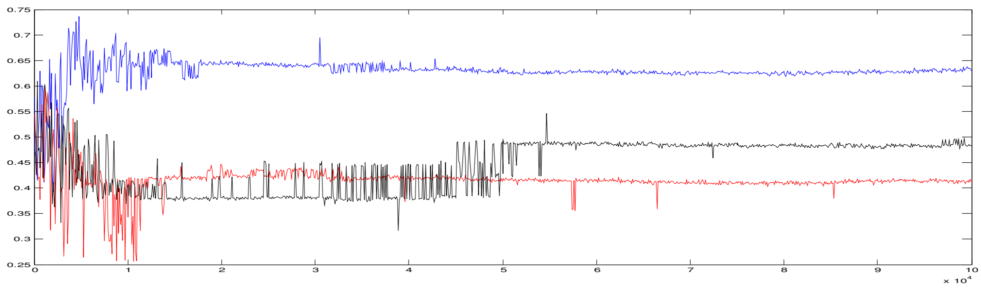
Tests are performed using different change severities. It is known [3] that: hypermutation performs well when the changes are of low severity; random initialization of some individuals is better for changes of higher severities; diploidy is useful in oscillating environments. Results show that as the severity of the changes increase, all of the hyperheuristics perform worse as expected. However, the adaptive hyperheuristic shows a slightly better adaptation for severer changes. Also, it is seen that the weights of the different methods follow the expected trends.

The results obtained in the tests are in keeping with the expected outcomes. Due to lack of space, only the plots of the weights achieved over the generations using the self-adaptive hyperheuristic in two environments of low and medium severities are displayed in Figure 1. In the first plot, it can be observed that the hypermutation method has an increasing weight value which means that its selection probability is also increasing. This is consistent with the fact that hypermutation is expected to be efficient for low severity changes. As expected also, weight values for the random initialization method improve as the severity is increased since severer changes cause the previous information gained by the search progress to be less relevant with the current global optimum.

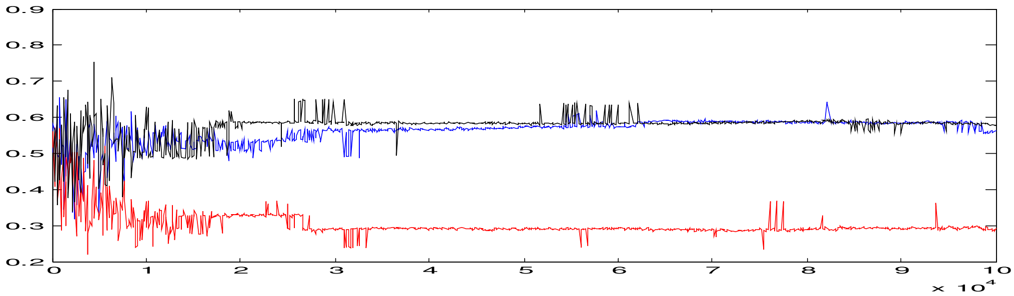
4. Conclusion and Future Work

The idea of exploiting the hyperheuristic approach for controlling basic dynamic environment methods seems as a promising technique to cope with dynamic environments of varying change severities. In this sense, this paper stands as a preliminary case study to examine the design and implementation of adaptive and self-adaptive hyperheuristics for dynamic problems.

As a future study, the basic methods mentioned above will be considered within more systematic experimental designs where more emphasis will be given also to parameter tuning and sensitivity analysis. More hyperheuristics and more sophisticated techniques for handling changing environments will also be explored. The effect of different change properties [3] other than change severity should be investigated too.



(a)



(b)

Figure 1. Self-adaptive weights evolved in the environment with severity of change values as a) 0.03, b) 0.20. The straight blue lines refer to weights of hypermutation, dashed red lines refer to weights of diploidy and black dotted lines indicate the weights of random initialization for the best individuals.

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