A Title of Your Paper

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Abstract

An abstract is a paragraph of 100–200 words that summarize the topic discussed in this paper and the major achievement(s) of the paper in order to attract attention of potential readers. DO NOT USE LISTS, TABLES, OR FIGURES IN ABSTRACT. The following is an example paragraph: This paper addresses a problem of searching on a sorted array of n distinct nonnegative integers. We present an algorithm for the search problem. The worst-case time complexity $t(n)$ *of the algorithm is analyzed and shown to be* $o(n)$ *by solving a recurrence system on* $t(n)$*. A naïve algorithm scans the entire array and results in* $\Theta(n)$ *time complexity. Hence, our algorithm improves the order of magnitude of the time complexity. Then, the extra space required by the algorithm beside its input is analyzed and shown to be* $O(1)$*. Thus, it implies an optimum bound of the space complexity for the problem.*

Keywords

algorithm; search; time complexity; space complexity; optimum bound

1. Introduction

In recent years, *genetic algorithms* (*GAs*) [1], [2], [3] have widely been recognized as an effective solving technique for complex problems in the real world [4]. For example, a bibliography [5] on applications of GAs even limited to only engineering includes over 1,400 papers as of April 1996. As GAs are getting a larger spectrum of applications, it becomes more crucial to develop a methodology for the design of GAs.

GAs can be regarded as a paradigm of algorithms in the sense that the GAs are parameterized and applicable to a variety of problems by instantiating the paradigm. There are the following 4 major components to be designed in GAs.

1) Coding: The representation of potential solutions which is a mapping scheme from a problem to the GA paradigm
2) Fitness Function: The quantified measure for quality of solutions which enables to differentiate “good” solutions from “bad” solutions
3) Configuration: A combination of operators which are applied to a population
4) Parameters: Population size, population structure, operators’ parameters (such as mutation rate), termination condition, etc.

In an optimization problem, the fitness function is usually given *a priori* as an objective function, although the objective function may slightly be modified so that constraints are incorporated into the fitness function appropriately.

Practitioners need a systematic way to design and implement “good” GAs for their particular problems quickly. To design good algorithms, we should be able to compare algorithms for the same problem and choose the best one with respect to a certain criterion. For deterministic, sequential algorithms (what we traditionally call “algorithms”), there are well-defined criteria such as space and time complexities. These criteria were generalized and applied to randomized algorithms as *average-case* computational complexities though, they are not suitable for evaluating the performance of GAs accurately.

The performance of GAs has been studied in terms of resultant fitness values and convergence primarily. For example, a number of papers investigated correlations between convergence speed and a particular parameter such as the population size and mutation rate. In many applications of optimization in practice (not necessarily real-time applications), however, a goal is to find a solution as good as possible "within a certain amount of time" [6]. With such a constraint on computational cost, it is not much critical to seek for convergence of a population. Furthermore, some applications such as robot path planning which will be discussed in Section 4 require the diversity of a population rather than the convergence in order to utilize the adaptivity of a GA. In addition, there may be a trade-off between solution quality and convergence, since a higher pressure (i.e., speed) to convergence tends to increase the possibility of premature convergence at a local optimum.

This paper proposes four performance measures of GAs: The *likelihood of optimality*, the *average fitness value*, the *likelihood of evolution leap*, and the *adaptivity*. The measures are defined so that they can be observed in simulation of GAs. They enable us to compare between different configurations of a GA for the same optimization problem and between different parameter settings in each configuration. Then, we present a case study in which a GA for robot path planning was tuned by using the measures in order to use it in motion planning of an underwater vehicle being developed at the University of Hawaii [7]. The performance of the GA was optimized through performance evaluation by using the proposed measures. With this experience in tuning of the GA by simulation, we propose a *process of tuning* based on techniques for *experimental design*. The process of tuning leads us to a systematic way for design and tuning of a GA. This is a step toward the development of a tool for automatic tuning of GAs.

This paper is organized as follows. Section 2 presents the terminology on GAs, defines the four performance measures, and introduces basic concepts of experimental design. Section 3 presents the case study which explains how we tuned a GA for robot path planning and shows simulation results on the performance of the GA. Section 4 proposes the process of tuning and discusses applications of techniques for experimental design to the process. Finally, Section 5 summarizes the paper.

2. Preliminaries

3. Algorithm Design

3.1. Key Idea

3.2. Pseudocode

3.3. Correctness Proof

4. Computational Complexity Analysis

4.1. Time Complexity

4.2. Space Complexity

4.3. Comparison with a Naïve Algorithm

5. Conclusion

This paper proposed the four performance measures of a GA: The likelihood of optimality, the average fitness value, the likelihood of evolution leap, and the adaptivity. The case study was presented in which a configuration of the GA for robot path planning was chosen, parameters of the GA were tuned and the performance was optimized through performance evaluation by using the measures. Finally, we proposed the process of systematic tuning based on techniques for the design of experiments. This is a step toward the development of a tool for automatic tuning of GAs [8], [9].

Based on the results presented in this paper, we are developing a GA for 3D online motion planning of the *Semi-Autonomous Underwater Vehicle for Intervention Missions* (SAUVIM) [10] that is capable of exploring up to 6,000 m in a deep ocean and manipulating objects with two arms.

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