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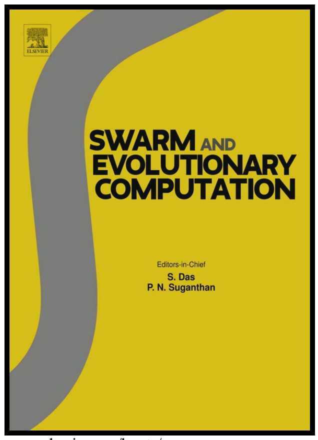

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Noisy Evolutionary Optimization Algorithms-A Comprehensive Survey

Pratyusha Rakshit, Amit Konar and Swagatam Das

Abstract— Noisy optimization is currently receiving increasing popularity for its widespread applications in engineering optimization problems, where the objective functions are often found to be contaminated with noisy sensory measurements. In absence of knowledge of the noise-statistics, discriminating better trial solutions from the rest becomes difficult in the "selection" step of an evolutionary optimization algorithm with noisy objective/s. This paper provides a thorough survey of the present state-of-the-art research on noisy evolutionary algorithms for both single and multi-objective optimization problems. This is undertaken by incorporating one or more of the five strategies in traditional evolutionary algorithms. The strategies include i) fitness sampling of individual trial solution, ii) fitness estimation of noisy samples, iii) dynamic population sizing over the generations, iv) adaptation of the evolutionary search strategy, and v) modification in the selection strategy.

Keywords— Evolutionary Optimization; Noise; Uncertainty; Sampling; Population Sizing; Fitness Estimation; Selection.

I. Introduction

Real world problems involving system design, control, planning, and scheduling are often formulated in the settings of an optimization problem with an aim to maximize system throughput/efficiency under the constraints on system resources. Typically, a physical process is characterized by a set of measurements and a set of estimators with a mathematical relationship between the measurements and the estimators. For example, in coordinated problem solving, such as box-pushing by twin robots [154], the range data obtained by the robots at any instance of time are the measurements, and the force and/or torque to be developed by the robot for a pre-determined movement of the box are the estimators. The objective functions, here, are energy and time required for local transportation of the box by the robots. The objectives include forces and torques as arguments.

The formulation in the present context is to compositely or independently optimize the two objectives. In single objective formulation, we may simply add the scaled objectives and attempt to optimize the resulting function. In multi-objective formulation, we attempt to optimize the energy and time objectives independently. The problem in the present context is to solve the single/multi-objective optimization problems, when the sensory range measurements are contaminated with noise. Traditional derivative based optimization techniques do not apply to the present problems because of inherent discontinuity of the noisy objectives. The paper addresses evolutionary approach to solve similar noisy optimization problems (NOPs).

Evolutionary algorithms (EAs) [16] aim at solving complex optimization problems by mimicking the Darwinian principle of the survival of the fittest [41]. EA commences from an initial population of trial solutions uniformly distributed over the search landscape. The trial solutions, representing the potential candidates of the optimization problem, are evolved through an adaptation phase, followed by a competitive selection phase for promotion to the next evolutionary generation. The relative merit of a trial solution is assessed by its corresponding objective function value, often called fitness. The 'selection' is an important step in EA as it filters quality solutions (with better fitness measure) from the pool of trial solutions while discarding poor solutions.

Although EA literature has witnessed a radically divergent perspective in solving real-world optimization problems, there is a distinct lack of studies exploring the issues of handling uncertainty in presence of noise. The other forms of uncertainties that might corrupt real-world optimization problems include data incompleteness, inaccuracy in mathematical modelling, environmental condition variation, and infeasible (non-realizable) solutions [42], [66], [89], [98]. Although EA is inherently robust to low levels of noise due to its distributed nature and its non-reliance on gradient information [42], the impact of noise becomes undesirable when it greatly affects the fitness of the trial solutions. The noisy fitness measurements of the trial solutions may adversely distress the performance of selection operation in preserving the true quality solutions over generations in an EA.

Mathematically, the noisy objective function of a trial solution $\vec{X}$ is represented by

$$f_{noisy}(\vec{X}) = f(\vec{X}) + \eta \tag{1}$$

where $f(\vec{X})$ is the true objective function value and η is the amplitude of the injected noise. It is evident from (1) that due to the noise-induced dynamic variation of the objective surface, the objective function returns different values when repeatedly evaluated for the same trial solution. In such circumstances, a trial solution of superior quality than the rest of the population may be declined by the selection operation to pass onto the next generation because of its seemingly poor (noisy) fitness estimate. Contrarily, an essentially poor solution with illusively good fitness may deceive the selection process to get accommodation in the next generation [5], [15], [22], [25], [26], [43], [48], [118], [133], [134], [135], [137], [161], [164], [192], [196].