Load Balancing for the Dynamic Distributed Double Guided Genetic Algorithm for MAX-CSPs

Sadok Bouamama, University of Tunis, Tunisia

Khaled Ghedira, University of Tunis, Tunisia

Nisrine Zaier, University of Tunis, Tunisia

ABSTRACT

The Dynamic Distributed Double Guided Genetic Algorithm (D^{3}G^{2}A) deals with Maximal Constraint Satisfaction Problems. The approach consists in creating agents cooperating together to solve problems. This paper aims to improve the D^{3}G^{2}A. The main purpose is to balance agent loads this distributed approach. The proposed approach will redistribute the load of Species agents more equally in order to improve the CPU time. This improvement allows not only reduction of the number of Species agents but also decreases communications agents cost. In this regard, a sub-population is composed of chromosomes violating a number of constraints in the same interval. Secondly, another proposed approach will redistribute the work load. This improvement allows diminution of inactive Species agents and it results in a balanced workloads. In fact, by analogy with social animal flocks, Species agents cooperate together to do all tasks in a reduced CPU time. Several comparisons are made about new approaches with the old version of the D^{3}G^{2}A. Results are promising.

Keywords: *Communications, Diminution, Dynamic Distributed Double Guided Genetic Algorithm, Maximal Constraint Satisfaction Problems, Species Agents*

INTRODUCTION

The constraint satisfaction problems (CSPs) formalism allow formulating and resolving many problems in artificial intelligence and operational research such as scheduling problems, resource allocation, frequency allocation, Vehicle routing problem etc.

A CSP is a triple (X, D, C) where.

- is a finite set of variables $\{x1, x2,\ldots, xn\}$.
  - D = $\{Dx1, Dx2, \ldots, Dxn\}$ set of domains of possible values of variables belongs to X.
  - C is a finite set of constraints of variables in X.

To resolve a CSP, we need an instantiation of all variables with values from their respective domains. This instantiation should satisfy

DOI: 10.4018/jalr.2010100105

Copyright © 2010, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

all constraints to get a good solution. To find a CSP solution is often a hard task. In fact, with some real life problems, the solution is either too expensive to get or even nonexistent. In addition, in some cases we need to express preferences and evolution of constraints in time. For such tasks, we should find an instantiation that maximizes the number of constraints. This CSP extension, said Max-CSPs, is the topic of this paper.

Max CSPs have been dealt with by complete or incomplete methods. Complete methods such as forward checking algorithm (Freuder & Wallace, 1992) and branch and bound algorithms (Meseguer, 1997; Wallace, 1996) are shown to be able to achieve an optimal solution. Nevertheless, the combinatorial explosion is an obstacle faced by theses systematic search methods. In fact, to ensure that the solution found is the optimal, systematic search algorithms would need to exhaust the entire problem space to establish that fact (Lau & Tsang, 2001).

However, incomplete ones are not able to guarantee that a solution can be found, and neither can they prove that a solution does not exist. They forgo completeness for efficiency. Many works such as (Langley, 1992) demonstrated on several large problems that what complete search algorithms fail to solve, incomplete ones efficiently conquer.

In fact, incomplete methods such as Simulated Annealing, Genetic Algorithms and Tabu Search allow escaping from local optima. Moreover, another incomplete but distributed method known as Distributed Simulated Annealing (DSA) has been shown to be efficiently applied to static Max-CSP, dynamic Max-CSP (Ghédira, 1994), Resource allocation problem (Bouamama & Ghedira, 2006). Distributing the centralized SA outperformed the solution's quality. Genetic Algorithm (GA) is a further well known incomplete method. It was frequently used in hard optimization problems (Tsang, EPK. 1993) solving multiprocessor scheduling problems (Bouamama & Ghedira, 2006). Similarly to distributing DSA, Centralized Genetic Algorithms (CGAs), known to be expensive, was also distributed to get better performances. The result was the Distributed Guided Genetic Algorithm (DGGA) (Jlifi & Ghédira, 2003). DGGA was enhanced by a new parameter called guidance operator. The latter allowed not only diversification but also an escaping from local optima. The result is referred to as Distributed Double Guided Genetic Algorithm (D^2G^2A) (Bouamama & Ghedira, 2008). Moreover, a further Improvement was performed through a Dynamic aspect in D^3G^2A (Bouamama & Ghedira, 2006; Zaier, Bouamama, & Ghédira, 2007).

The purpose of this paper is to outperform D^3G^2A. The present paper describes D^3G^2A, its strong and weak points. Next, we set the problems and we formulate our proposition. Experimental results are presented and the performance of the two heuristics are compared and analyzed. Finally, a conclusion is given.

D^3G^2A

Basic Principles

D^3G^2A draws basically on the concept of both Species and ecological niches. The Species consists of several organisms having common characteristics whereas the ecological niche represents the task performed by a given Species (Bouamama & Ghedira, 2006). Goldberg sets that the sexual differentiation based on specialization, via both the building of Species and the exploitation of ecological niches, provides good results (Goldberg, 1989). Some methods have been settled in order to favor the building of ecological niches in GAs (Goldberg, 1989).

So, the idea here is to partition the initial population into sub-populations and to assign each one of them to an agent called Species agent. A given sub-population consists of chromosomes having their fitness values in the same range. This range, said FVR (for fitness values range), is the specificity of the Species agent $Species_{FVR}$. Species agents are in interaction, in order to reach an optimal solution for the problem. For this reason, each Species agent performs its own GA. The latter is guided by both template concept and min-conflict heuristic

Copyright © 2010, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

17 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/article/load-balancing-dynamic-distributed-double/49684

Related Content

Conceptual and Practical Aspects of the aiNet Family of Algorithms
Fabrício O. de França, Guilherme P. Coelho, Pablo A.D. Castro and Fernando J. Von Zuben (2010). *International Journal of Natural Computing Research (pp. 1-35).*
www.irma-international.org/article/conceptual-practical-aspects-ainet-family/41942/

Structural Learning of Genetic Regulatory Networks Based on Prior Biological Knowledge and Microarray Gene Expression Measurements
Yang Dai, Eyad Almasri, Peter Larsen and Guanrao Chen (2010). *Handbook of Research on Computational Methodologies in Gene Regulatory Networks (pp. 289-309).*
www.irma-international.org/chapter/structural-learning-genetic-regulatory-networks/38240/

Supercritical Pitchfork Bifurcation in Implicit Regression Modeling
Stan Lipovetsky (2010). *International Journal of Artificial Life Research (pp. 1-9).*
www.irma-international.org/article/supercritical-pitchfork-bifurcation-implicit-regression/49680/

Impact of Olfaction on Information Recall: Perspectives from an Empirical Study
Gheorghita Ghinea and Oluwakemi Ademoye (2013). *Human Olfactory Displays and Interfaces: Odor Sensing and Presentation (pp. 446-456).*
www.irma-international.org/chapter/impact-olfaction-information-recall/71939/

An Application of Genetic Programming to Forecasting Foreign Exchange Rates
Muneer Buckley, Zbigniew Michalewicz and Ralf Zurbruegg (2010). *Nature-Inspired Informatics for Intelligent Applications and Knowledge Discovery: Implications in Business, Science, and Engineering (pp. 26-48).*
www.irma-international.org/chapter/application-genetic-programming-forecasting-foreign/36310/