An Agent-Based Collaborative Evolutionary Model for Multimodal Optimization

Rodica I. Lung
Babes-Bolyai University
Faculty of Economics and Business Administration
Cluj Napoca, Romania
rodica.lung@econ.ubbcluj.ro

Camelia Chira
Babes-Bolyai University
Department of Computer Science
Cluj Napoca, Romania
cchira@cs.ubbcluj.ro

D. Dumitrescu
Babes-Bolyai University
Department of Computer Science
Cluj Napoca, Romania
ddumitr@cs.ubbcluj.ro

ABSTRACT

A novel approach to multimodal optimization called Roaming Agent-Based Collaborative Evolutionary Model (RACE) combining several evolutionary techniques with agent-based modeling is proposed. RACE model aims to detect multiple global and local optima by training a multi-agent system to employ various evolutionary techniques suitable for a specified multimodal optimization problem. Agents can exchange information during the search process enabling a cooperative search of optima between several populations evolving independently. Redundant search by multiple agents is avoided by having them communicate and negotiate about the space region searched. An agent can request and receive from another agent valuable information and genetic material for a better search of a certain region in the environment. Performance of the proposed agent-based collaborative evolutionary model is compared by means of numerical experiments with rival evolutionary techniques.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*intelligent agents, multiagent systems*

General Terms

Algorithms

Keywords

evolutionary multimodal optimization, multi-agent systems, collaborative search

1. INTRODUCTION

Multimodal optimization refers to detecting all global and local optima of a problem. Evolutionary algorithms have been successfully engaged for multimodal optimization problems as they are highly adaptable and able to maintain a set of possible solutions. However due to elitist versus population diversity the balance between detecting all optima and maintaining while avoiding redundant search is very weak.

A novel approach to multimodal optimization is proposed exploring the benefits of evolutionary techniques in conjunction with the potential of multi-agent systems for communication, pro-activeness, autonomous behavior and flexible interactions in an environment.

The paper introduces the *Roaming Agent-Based Collaborative Evolutionary Model (RACE)* for solving multimodal optimization problems. RACE technique aims to detect all optima of a problem using a set of collaborative agents able to engage various evolutionary techniques to solve a given problem. Each agent has the capability of evolving a population of individuals using a certain evolutionary algorithm. Agents collaborate by exchanging information about the environment and the detected solutions. A global interactive search process emerges enabling a flexible and efficient identification of local and global optima. The exploration of the same search space region by multiple agents is avoided by having agents communicate and negotiate about the space region searched.

2. MULTIMODAL OPTIMIZATION

Most real world problems present more than one local optimal solution. Such problems occur in various fields including pattern recognition, fixed point theory, classification and game theory.

For such problems we are interested not only in finding one or more global optima but in identifying the set of all acceptable solutions. The problems requiring the detection of all local and global optima are called multimodal optimization problems (MMOPs).

From the point of view of the number and distribution of the optima, MMOPs can be classified in two categories:

- MMOPs presenting a discrete set of optima: these problems are addressed in this paper.
- MMOPs having an infinite number of optima: for example optima can be displayed in a circular manner similar to the waves of a lake when a stone is thrown in it.

Due to their high adaptability evolutionary algorithms are very good candidates for approaching multimodal optimization. One of their main advantages it that theoretically they

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
GECCO'08, July 12–16, 2008, Atlanta, Georgia, USA.
Copyright 2008 ACM 978-1-60558-131-6/08/07 ...$5.00.

may be designed to detect and to maintain a *set* of solutions during one run.

When dealing with multiple optima from an evolutionary optimization point of view several issues arise. The first one is how to assess/decide when or if a local optimum has been detected. Simple comparison of fitness values of two individuals is not relevant: if one of them represents a global optimum and the other a local optimum their comparison may lead to the discarding of the second one. Then the second issue arises: once detected, how to maintain the local optima during the evolution process?

Elitism versus diversity preservation are classical issues in evolutionary computation. To these it is added the one of deciding which are the elitist individuals within a population when the goal is to detect also the local optima.

Several evolutionary approaches to multimodal optimization have been proposed. From the output point of view, evolutionary techniques dealing with multiple solutions can be divided in two classes:

- The first class consists of the algorithms that provide as an output a population containing individuals gathered around the optima. Most classical approaches belong to this class. A human decision maker is needed to extract the local optima from the provided set. The number of optima can not always be deduced from the output population. Among these approaches the most widely used are the Fitness Sharing based techniques [5] and the Crowding methods [7, 10, 14].
- In the second class the output of the algorithm consists of a population containing only the optima detected. Sometimes an external population or an archive is used to store these optima. Generally these methods also provide the correct number of optima for the problem. In this class we find somewhat recent approaches such as the Adaptive Elitist Genetic Algorithm [8], Genetic Chromodynamics [4], Roaming technique [9] or the Multiresolution Multipopulation Differential Evolution [17].

The proposed RACE model belongs to the second class mentioned above, i.e. providing the location and number of detected optima.

3. ROAMING OPTIMIZATION

Roaming technique is a recently proposed [9] evolutionary technique for multimodal optimization. Roaming technique detects multiple optima by using several subpopulations evolving in isolation. Potential optima are saved into an external population called *archive*.

Subpopulations are performing the exploration of the search space while members of the archive perform the exploitation part.

Roaming solves the problem of deciding when an optimum has been detected by using a stability measure for subpopulations. This stability measure enables the characterisation of subpopulations as stable or unstable. Unstable subpopulations evolve in isolation until they become stable. The best individual in a stable subpopulation is considered to be a potential local optimum.

The number of subpopulations is a parameter of the algorithm and it is not related to the expected number of local optima. Subpopulations are not restricted to a certain area of the search space. This confers flexibility and robustness to the search mechanism.

Potential optima are saved into the *archive*. Stable subpopulations are spread over the search space in order to detect other optima.

The archive contains individuals corresponding to different optimum regions. The exploitation task is realized by refining the elite individuals in the archive. Several archiving strategies have been proposed in order to ensure that each archive member corresponds only to one optimum region.

The output of the algorithm is represented by the archive - the set of elitist individuals containing local optima.

4. MULTI-AGENT SYSTEMS

A multi-agent system (MAS) employs several agents capable of interacting with each other to achieve objectives [16, 2, 1]. The benefits of such an approach include the ability to solve large and complex problems, interconnection and interoperation of multiple existing legacy systems and the capability to handle domains in which the expertise is distributed [6, 1, 11].

Interoperation among autonomous agents of MAS is essential for the successful location of a solution to a given problem [13, 2]. Agent-oriented interactions span from simple information interchanges to planning of interdependent activities for which cooperation, coordination and negotiation are fundamental.

Coordination is necessary in MAS because agents have different and limited capabilities and expertise [11]. Agents have to coordinate their activities in order to determine the organizational structure in a group of agents and to allocate tasks and resources. Furthermore, interdependent activities require coordination (the action of one agent might depend on the completion of a task for which another agent is responsible).

Negotiation is essential within MAS for conflict resolution and can be regarded as a significant aspect of the coordination process among autonomous agents [1, 11].

Agents need to communicate in order to exchange information and knowledge or to request the performance of a task as they only have a partial view over their environment [16, 2].

Characterized by computational efficiency, reliability, extensibility, robustness, maintainability, responsiveness, flexibility and reuse, multi-agent systems promote conceptual clarity and simplicity of design [6, 13].

Regarding the use of simulated evolution in designing intelligent agents, a current state of art can be found in [3]. Int

5. PROPOSED RACE MODEL

A novel agent-based evolutionary technique for multimodal optimization is proposed. The introduced technique is called *Roaming Agent-Based Collaborative Evolutionary Model (RACE)*. It is essentially a multi-agent system designed to solve a given optimization problem by engaging various evolutionary techniques and exchanging intermediary information and genetic material. RACE represents a generalization of the Roaming technique for multimodal optimization.

Each agent of the RACE system explores the search space using a certain method - known at design time - to evolve a population of individuals. These agents are called *Roaming Evolutionary (RE) Agents*. The number of RE agents is a parameter of the RACE algorithm and equals the number of populations evolving in parallel. Furthermore, there will be as many societies of RE agents as the number of evolutionary techniques employed by the RACE system. It is possible to engage only one evolutionary method for all RE agents in the system with potentially meaningful interactions.

Communication among RE agents is very important for flexible and efficient global search process. A RE agent is able to detect with the help of a *Directory Facilitator (DF) Agent* if another RE agent is currently exploring the same search space region. In such a situation, the two RE agents can engage in a negotiation process that will quickly determine only one agent as the main explorer of that region. The agent negotiation is influenced by the number of individuals in the space neighborhood that each agent controls. The RE agent that wins this negotiation process can receive from the other RE agent valuable genetic material consisting of the relevant individuals from its population.

Potential optima detected by an RE agent is forwarded for storage purposes to a specialized agent called *Optima Manager (OM) Agent*. The OM agent has the capability of managing the set of potential solutions by deciding if a solution received from an RE agent qualifies as potential optima.

The proposed RACE model relies on the following classes of interacting agents:

- *Roaming Evolutionary (RE)* agent has the objective of detecting global and local optima of the given optimization problem using an evolutionary technique. RE agents are able to collaborate with each other, to register with the DF agent and to communicate obtained solutions to the OM agent.
- *Directory Facilitator (DF)* agent has the capability of keeping a Yellow Pages type of service for the system. There are two main facilities provided by DF agent as follows: (i) agents can register (and deregister) their situation; and (ii) agents can query the DF to find out which agent or agents (if any) services the same region.
- *Optima Manager (OM)* agent has the objective of managing the set of potential solutions of the given problem being. It has the ability of accepting or rejecting requests from RE agents to store potential optima and to refine stored potential optima.

The RACE system uses several RE agents but only one instance of the DF and OM agents.

6. RACE PROTOTYPE MODEL IMPLEMENTATION

The proposed Roaming Agent-Based Collaborative Evolutionary model has been evaluated through the implementation of a prototype. Furthermore, the implemented RACE algorithm has been engaged in solving a multimodal optimization problem and numerical experiments and comparisons are presented in the next section.

The RACE propotype model implements the main types of agents described in the previous section. All RE agents use an evolutionary algorithm in order to detect local optima. In the proposed implementation an EA using tournament selection, two-point crossover and uniform mutation is used. RE agents collaborate using the DF agent. RE agents use the DF in order to decide if their search does not overlap with the search of other agents.

All potential optima are forwarded for storage purposes to the OM agent which decides whether to store it or not. The OM agent is also responsible with refining the stored potential optima.

The RACE agents implement several features used by Roaming technique and specific agent-based features such as communication of genetic material and the use of a directory facilitator.

6.1 Stability measure

A *stability measure* is used within Roaming for determining whether a population of individuals has located a potential optimum.

By evolving subpopulation P of individuals for n_{it} generations a new subpopulation $P^{'}$ having the same size as P is obtained.

The number n_{it} of iterations the subpopulations evolve in isolation until their stability is measured is a parameter of the algorithm called the *iteration parameter*.

Let x^* be the best individual in the parent population P. We define operator B as the set of individuals in the offspring in population $P^{'}$ that are better then x^*:

Using the cardinality of the set B the stability measure $SM(P)$ of population P is defined.

Definition 6.1. *Stability measure of the subpopulation P represents the number $SM(P)$ defined as*

$$SM(P) = 1 - \frac{card\, B(x^*)}{card\, P},$$

where x^* is the best individual in P and card A represents cardinality of the set A.

Stability measure of a population P has the following properties:

(i) $0 \leq SM(P) \leq 1$;

(ii) If $SM(P) = 1$ then x^* is a potential local optimum.

Definition 6.2. *An RE agent evolving a population P is called σ-*stable *if $SM(P) \geq \sigma$ holds, where $0 \leq \sigma \leq 1$. A 1-stable stable RE agent is called a* stable *RE agent.*

Remarks 6.1. (i) *A RE agent evolving a population P is called σ-unstable if it is not σ-stable.*

(ii) *A $1-$unstable RE agent is called an* unstable *agent.*

Within RACE a RE agent evolves a population of individuals by the rules of an EA until it reaches stability. A stable RE agent transmits to the OM the information about the location of its best individual (considered to be a potential optimum). After that the RE agent automatically restarts the search of its population.

6.2 The Optima Manager

The Optima Manager is an agent representing the archive used by the Roaming technique. The duties of the OM are as follows:

- to store the potential optima detected;

- to refine the potential optima detected;
- to receive information from stable RE agents regarding new potential optima and decide weather they are to be stored or not.

The OM has to fullfill the following requirements:

- each individual in the OM corresponds to *one* optimum region;
- to each optimum region there is at most one individual assigned.

Thus for each optimum there should be only one individual in the OM approximating it. The number of individuals in the OM should be less than or equal to the number of optima of the problem. Within Roaming several methods for archiving solutions have been proposed:

- The first one (M1) uses a distance parameter δ_s in order to asses whether a new potential optimum represents a new optimum region or not.
- The second method (M2) completely eliminates this parameter by using a 'valley detection' scheme.
- The third one (M3) combines the first two in order to take advantage of the robustness of the second method but also to reduce its computational complexity.

In the present implementation of RACE the second method (M2) hase been employed by the OM in order to decide if a new potential optimum needs to be stored.

M2 uses a 'valley' detection mechanims proposed by Ursem [15] that - unlike other strategies - does not require a distance parameter related to the problem. A new individual is accepted by the OM if there exists a 'valley' between him and any other individual in the OM. If between the candidate individual and another individual in the OM no 'valley' is detected, the OM preserves the best of them.

Unlike within the Cultural Algorithms [12] with which RACE may seem similar, the OM does not influence the search of the RE agents in any way.

6.3 OM refinement of solutions

The OM accepts potential optima from stable RE agents. Potential optima represent individuals that are close to a local optimum, or that belong to a new optimum region. However, they may not represent good approximations of the corresponding optima, therefore they need to undergo a refinement process. Within Roaming this refinement takes place by using a mutation operator. [9]

Each individual in the OM is mutated: an offspring is created and evaluated. If the fitness value of the offspring is better than that of the parent then the offspring is considered to be accepted in the OM - as a new individual - by going trough the decision process. This is a precaution taken to avoid losing an optimum if the offspring is created on a different optimum region than the parent.

6.4 Communication between RE agents

Within Roaming technique subpopulations evolve in isolation troughout the entire search process. The main contribution of the RACE model is the use of communication protocols between agents in order to enhance their capabilities, avoid redundant search and improve their results.

Within RACE, RE agents use a Directory Facilitator agent to find if other agents are converging towards the same optimum region. One way to test this is to compute the distance between the best individuals in the populations evolved by two agents. If two agents consider that they are converging towards the same optimum they start a negociation. One of the RE agents will continue the search in the promissing region by keeping best individuals from both agents while the other RE agent will continue its search using the rest of the individuals. Thus one of the RE agents will converge more rapidly with the help of the genetic material provided by the second one which was also going to explore the same region while the other will hopefully redirect its search with the diversity provided by the individuals resulting from negociation.

Within the present proposed prototype implementation the agents first decide their future role (which one will continue the search in the promissing region) and then each agent proposes for competition a randomly chosen individual from its population. The RE agent remaining in the optimum region will keep the best individual from the two. Other communication means between agents can be designed.

6.5 RACE model

RACE model is based on the Roaming technique for multimodal optimization. It uses several communicating Roaming Evolutionary Agents that are locating the promissing regions by using an evolutionary algorithm. The RE agents share information using a Directory Facilitator agent. Negociations take place between agents that 'believe' that their search will converge towards the same optimum region.

An Optima manager agent is used to maintain the optima detected. It accepts or not individuals from stable RE agents and refines individuals that correspond to optimum regions.

At the beginning of each iteration RE agents subscribe to the DF agent and check if any the search of any other agent converges towards the same region. If so, negociation between RE agents takes place. After that, each agent evolves its population of solutions for a number n_{it} of iterations and the stability measure is computed. Stable agents transmit the location of their best individual to the OM which accepts it or not as a new optimum and then restart the search of their populations. Unstable agents continue the search.

The search stopes when a maximum number of fitness function evaluations is reached. The parameters used by RACE are listed as follows:

N - number of agents
$Popsize$ - population size of each agent
$Maxeval$ - maximum number of
fitness function evaluations allowed
n - iteration parameter
p_c, p_m -crossover probability and mutation rate

One of the most important features of this method is that not only it locates optima but also provides their number and positions unlike other methods that only give a set containing optima among other individuals.

7. EXPERIMENTAL RESULTS

Results obtained using RACE are compared with those of its sibling Roaming technique as reported in [9] in order to assess the impact of the agent-based features introduced.

The Peaks1-5 functions as presented in [9] are used:

- Problem Peaks1 is defined on $[-100, 100]^2$ and has three peaks of different heights.
- Problem Peaks2 has 10 peaks of varying heights. The minimum distance between two peaks is 36.055 and the maximum is 197.98. No basis function is used.
- Problem Peaks3 is a 15-peaks function defined on $[-10, 10]^2$. All peaks have the same height. Minimum distance between peaks is 3.18 and the maximum is 21.98.
- Problem Peaks4 is similar to $peaks3$ benchmark, the only difference appearing regarding the peaks heights
- Problem Peaks5 is defined on $[-100, 100]^{10}$. It has 4 peaks situated at a minimum distance between them of 125.29 and a maximum one of 333.46 . The peaks have the same height of 100.

7.1 Performance measures

Several performance measures for multimodal search operators have been used in literature. The following performance indicators are considered throughout this work:

- peaks ratio p_r - considered as the number of optima as reported by the algorithm divided by the real number of optima of the problem
- real peaks ratio rp_r [14] - considered as the number of optima actually detected by the algorithm divided by the real number of optima. An optimum is considered to be detected if there exists one individual in the output population within 0.5 distance to it.
- average minimum distance to the real optima
- standard deviation of the averages minimum distances to real optima SD over a number of runs. It indicates the variations of average minimum distances over different runs.

Most evolutionary approaches only provide a population with individuals concentrated around optimum regions. It is up to the human decision maker to establish if all optima are detected and if all concentrations represent optimum regions or not.

Although some population may contain local optima, it may be difficult to assess which are these optima among the other individuals in the populations. It is therefore important for a multimodal evolutionary algorithm to provide not only a distinct set of optima but also their number. That is why we have considered two indices connected to the number of optima: the peaks ratio (p_r) and the real peaks ratio (rp_r). Although they have similar expressions, one is computed taking into account the number of optima reported by the algorithm, while the other the number of optima detected (number of individuals within 0.5 distance to optima).

In the following section, the above indicators are averaged above 30 runs for each experiment.

Table 1: Roaming : Setting parameters for Peaks1-5 tests

Problem	Size of subpop.	Valley detection
Peaks1	10	10
Peaks2	3	30
Peaks3	3	30
Peaks4	3	30
Peaks5	20	15

Table 2: Roaming: Common parameters for Peaks1-5

Parameter	Value
Number of iterations	1
Number of subpopulations/agents	10
Mutation rate	0.05

7.2 Parameter settings

The algorithms were run up to maximum 50000 fitness function evaluations. Average and standard deviations of distances to optima are presented as well as for the peaks ratio and real peaks ratio. The common parametters of Roaming and RACE have been given the same value for fair comparison.

Parameter settings for the seven benchmarks are presented in tables 1 and 2.

7.3 Results

Tables 3 - 7 present descriptive statistics related to the five benchmarks, i.e. the values for the mean of the average distances to optima over the 30 runs, the corresponding standard deviation, the minimum and median of the average distances to optima, the mean and standard deviation of the peaks ratio and the mean and standard deviation of the real peaks ratio.

Descriptive statistics presents RACE to outperform Roaming for the tested functions. Median values of D indicate that for all the problems RACE located the optima more accurately than Roaming indicating the use of agent-based feature as a promissing research area.

8. CONCLUSIONS AND FURTHER WORK

A new multi-agent system constructed based on an evolutionary technique for multimodal optimization called Roaming is presented. The proposed model, Roaming Agent-Based Collaborative Evolutionary model (RACE) uses three types of agents to locate and store local and global optima of a given problem.

Table 3: Descriptive statistics related to problem Peaks1

Indicator	RO	RACE
Mean of D	0.246	**7.77E-7**
StDev of D	0.779	**2.23E-7**
Min of D	3.907E-5	**2.6E-7**
Median of D	6.805E-5	**7.87E-7**
Mean of rp_r	0.966	**1**
StDev of rp_r	0.105	0
Mean of p_r	**1**	**1**
Stdev of p_r	0	0

Table 4: Descriptive statistics related to problem Peaks2

Indicator	RO	RACE
Mean of D	8.414	**6.89**
StDev of D	4.000	4.62
Min of D	0.752	**3.94E-6**
Median of D	8.53	**6.69**
Mean of rp_r	0.75	**0.87**
StDev of rp_r	0.108	0.07
Mean of p_r	0.86	**0.87**
Stdev of p_r	0.069	0.07

Table 5: Descriptive statistics related to problem Peaks3

Indicator	RO	RACE
Mean of D	3.518E-4	**8.47E-6**
StDev of D	5.219E-5	1.01E-6
Min of D	2.598E-4	**7E-6**
Median of D	3.509E-4	**8.51E-6**
Mean of rp_r	**1**	**1**
StDev of rp_r	-	0
Mean of p_r	1	1.006
Stdev of p_r	-	0.02

Table 6: Descriptive statistics related to problem Peaks4

Indicator	RO	RACE
Mean of D	**1.919E-3**	0.02
StDev of D	3.196E-3	0.07
Min of D	3.114E-4	**6.64E-6**
Median of D	4.409E-4	**8.52E-6**
Mean of rp_r	**1**	0.99
StDev of rp_r	-	0.02
Mean of p_r	**1**	0.99
Stdev of p_r	-	0.02

Table 7: Descriptive statistics related to problem Peaks5

Indicator	RO	RACE
Mean of D	8.565	**8.5E-4**
StDev of D	7.323	6.9E-5
Min of D	0.044	**6E-4**
Median of D	11.00	**8.5E-4**
Mean of rp_r	0.775	**1**
StDev of rp_r	0.184	0
Mean of p_r	**1**	1.008
Stdev of p_r	-	0.04

The Roaming Evolutionary Agents are 'roaming' the space in order to find promissing regions using an evolutionary algorithm. They are using a stability measure to decide when to stop/restart the search. A directory facilitator is used by the RE agents to check if two of them are converging towards the same optimum region. Agents overlapping negociate and exchange genetic material in order to avoid redundant search.

Numerical experiments show RACE to outperform Roaming for the tested benchmarks. Future tests considering different communication mechanisms between agents are considered.

9. REFERENCES

[1] Jeffrey M. Bradshaw. An introduction to software agents. In Jeffrey M. Bradshaw, editor, *Software Agents*, pages 3–46. AAAI Press / The MIT Press, 1997.

[2] Chira, O., Chira, C., Roche, T., Tormey, D., Brennan, and A. An agent-based approach to knowledge management in distributed design. *Journal of Intelligent Manufacturing*, 17(6):737–750, December 2006.

[3] K.A. De Jong. Evolving intelligent agents: A 50 year quest. *Computational Intelligence Magazine, IEEE*, 3(1):12–17, February 2008.

[4] D. Dumitrescu. Genetic chromodynamics. *Studia Universitatis Babes-Bolyai, Informatica*, XLV(1):39–49, 2000.

[5] D.E. Goldberg and J. Richardson. Genetic algorithms with sharing for multimodal function optimization. In Grefenstette, editor, *Genetic algorithms and their Applications ICCGA'87*, pages 41–49, 1987.

[6] Nicholas R. Jennings. On agent-based software engineering. *Artificial Intelligence*, 177(2):277–296, 2000.

[7] K. A. D. Jong. *An analysis of the behaviour of a class of genetic adaptive systems.* PhD thesis, University of Michigan, 1975.

[8] K. S. Leung and Y. Liang. Adaptive elitist-population based genetic algorithm for multimodal function optimization. In *GECCO 2003, LNCS 2723*, pages 1160–1171. Springer-Verlag Berlin Heidelberg, 2003.

[9] Rodica Ioana Lung and D. Dumitrescu. A new evolutionary model for detecting multiple optima. In *GECCO '07: Proceedings of the 9th annual conference on Genetic and evolutionary computation*, pages 1296–1303, New York, NY, USA, 2007. ACM.

[10] S. W. Mahfoud. *Niching methods for genetic algorithms.* PhD thesis, University of Illinois at Urbana Champaign, Illinois Genetic Algorithm Laboratory, 1995.

[11] H. S. Nwana, L. C. Lee, and N. R. Jennings. Coordination in software agent systems. *The British Telecom Technical Journal*, 14(4):79–88, 1996.

[12] R.G. Reynolds and M. Ali. Computing with the social fabric: The evolution of social intelligence within a cultural framework. *Computational Intelligence Magazine, IEEE*, 3(1):18–30, February 2008.

[13] Stuart Russell and Peter Norvig. *Artificial Intelligence: A Modern Approach.* Prentice Hall, second edition, 2003.

[14] Rene Thomsen. Multimodal optimization using crowding-based differential evolution. In *Proceedings of the 2004 IEEE Congress on Evolutionary Computation*, pages 1382–1389, Portland, Oregon, 20-23 June 2004. IEEE Press.

[15] Rasmus K. Ursem. Multinational evolutionary algorithms. In Peter J. Angeline et al., editor, *Proceedings of the Congress of Evolutionary Computation (CEC-99)*, volume 3, pages 1633–1640, USA, 6-9 July 1999. IEEE Press.

[16] Michael Wooldridge. *Introduction to MultiAgent Systems*. John Wiley & Sons, June 2002.

[17] Daniela Zaharie. Extensions of differential evolution algorithms for mulitmodal optimization. In Dana Petcu et al., editor, *SYNASC*, pages 523–534, September 2004.