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Sensor deployment for fault diagnosis using a new discrete optimization algorithm

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ABSTRACT

Optimal allocation of the sensor in a wireless sensor network (WSN) is required to have a satisfactory fault diagnosis within the system. In fact, the sensor nodes in the network should be located in an arrangement to maximize the failure diagnosis. In this paper, the sensor deployment optimization to diagnose the distributed failures in a wireless unmanned aerial vehicles (UAVs) network has been studied. In this way, a novel evolutionary optimization algorithm inspired by the gases Brownian and turbulent rotational motion is utilized which is called Discrete Gases Brownian Motion Optimization (DGBMO) algorithm. An integer linear programming (ILP) approach is used to formulate the sensor deployment. Then the sensor deployment optimization is solved by DGBMO as well as generic ILP solvers and Boolean satisfiability-based ILP solvers. The results show that DGBMO is suitable for sensor disposition optimization especially in large-sized UAV networks.

1. Introduction

Development of appropriate algorithms for solving complex problems such as optimization and search problem, has traditionally been one of the most important issues in Computer Science. The global optimization methods have been applications in many fields of science for example business and engineering. The main concern for the optimization techniques is if there would be several local optimums in the system. During the last decade, evolutionary algorithms (EAs) have been applied to optimization problems in a variety of areas [1]. In artificial intelligence, an EA is a generic population-based meta-heuristic algorithm which has a subset of evolutionary computations. In fact, a typical EA model using the evolution process of biological populations can adapt to the changing environment to find the optimum value through the candidate solutions. In other words, EAs are optimization techniques that work on a set of population or individuals by applying stochastic operators to them in order to search an optimal solution.

Several different EAs have been developed for optimization which among them we can point to the following. The first is Genetic Algorithm (GA) proposed by Holland [2] which is inspired from the biological evolutionary process. Particle Swarm Optimization algorithm proposed by Kennedy and Eberhart [3], in 1995. Simulated Annealing [4] is designed by use of thermodynamic effects and Cultural Evolutionary algorithm (CE), developed by Reynalds and Jin [5], in the early 1990s. The ant colony optimization algorithm (ACO) mimics the behavior of ants foraging for food [6]. Differential evolution (DE) is another optimization algorithm. The DE method is originally due to Storn and Price [7] and works on multidimensional real-valued functions which are not necessarily continuous or differentiable. Harmony search (HS) is a phenomenon-mimicking algorithm inspired by the improvization process of musicians [8]. Artificial Immune System (AIS) simulate biological immune systems [9]. Table 1 shows some of the new evolutionary algorithms.

As a newly developed type of meta-heuristic algorithm, the charged system search (CSS) is introduced for design of structural problems [24]. The Gravitational Search Algorithm (GSA) presented by Rashedi et al. [25] is introduced using physical phenomena.

The new algorithm has been proposed by Atashpaz-Gargari and Lucas [26] which has not inspired natural phenomenon, but of course from a socio-human phenomenon. This algorithm has looked at imperialism process as a stage of human's socio-political evolution.

A new algorithm presented in [27,28] which is called Gases Brownian Motion Optimization (GBMO) algorithm. GBMO algorithm using model characteristic gas molecules and their movements, proposed efficient algorithm to solve optimization problems.

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Table 1
New evolutionary algorithms.

Chuanwen et al.	2005 [10]	A hybrid method of chaotic particle swarm optimization and linear interior for reactive power optimization.
Sha et al.	2006 [11]	Tabu search algorithm for the shop scheduling.
Shelokar et al.	2007 [12]	Particle swarm and ant colony algorithms hybridized for improved continuous optimization.
Liu et al.	2007 [13]	A fuzzy adaptive turbulent particle swarm optimization.
He et al.	2007 [14]	Simulated annealing for the constrained optimization.
Ge et al.	2008 [15]	Artificial immune system for the shop scheduling.
Kwong et al.	2008 [16]	The hybrid fuzzy least squares regression approach to modeling manufacturing processes.
Kavehand et al.	2009 [17]	Particle swarm optimizer, ant colony strategy and harmony search scheme hybridized for optimization of truss structures.
Chen et al.	2010 [18]	Unconstrained global optimization.
Abdel-Kader	2010 [19]	Genetically improved PSO algorithm for efficient data clustering.
Chan et al.	2010 [20]	Neural fuzzy networks and genetic algorithms for optimization of fluid dispensing for electronic packaging.
Hashemi et al.	2011 [21]	A note on the learning automata based algorithms for adaptive parameter selection in PSO
Thangaraj et al.	2011 [22]	Particle swarm optimization: hybridization perspectives and experimental illustrations.
Chan et al.	2011 [23]	A backward elimination based genetic programming for reducing over-fitting in manufacturing process modeling.

In this paper, we consider a different method based on artificial intelligence (AI) for solving the fault diagnosis problem. We present a new evolutionary algorithm for identifying faults in a wireless sensor network. To achieve this end, a new discrete optimization algorithm based on principles from physics and gases Brownian motion has been developed called Discrete Gases Brownian Motion Optimization (DGBMO). This algorithm is presented by modeling of gases Brownian motion and Learning Automata.

This paper addresses sensor deployment problems for distributed failure diagnosis in wireless UAV networks where nodes must agree on the fault of another node. We introduce a new evolutionary algorithm for solving this problem in sensor deployment problem.

Basically, a fundamental issue of any wireless sensor network is sensor deployment [29]. Failure diagnosis in such a wireless network is an important problem which is related to the sensor deployment. In a wireless network, each node must agree on the fault of the other nodes. In general, failure diagnosis strategies can be classified into the following two categories:

- *Classical model*. This strategy presents algorithms for the fault diagnosis in a directed-graph-based model [30].
- *Comparison-based diagnosis model*. This strategy presents algorithms for fixed and time-varying network topologies such as asymmetric comparison model [31], symmetric comparison model [32], and Artificial Immune Systems (AIS) [33]. In [34], generalized comparison model is presented. In Table 2, a summary of some previous research for system fault diagnosis are shown.

A new algorithm is presented in [40] which used the integer linear programming (ILP) approach for diagnosing a node failure of networks. This paper used generic ILP solvers (CPLEX) and Boolean satisfiability-based ILP solvers (PBS) for solving this problem.

This paper investigates deployment strategies for diagnosing a node failure of sensor networks. Sensor placement is formulated using an integer linear programming (ILP) approach and is solved by a new evolutionary algorithm. The proposed algorithm is called Discrete Gases Brownian Motion Optimization (DGBMO).

Table 2
Analytical approaches.

Parameter estimation	[35]
Parity equations based on analytical (or functional) redundancy	[36]
Fault-symptom based	[37]
Comparison-based diagnosis model	[38]
Probabilistic diagnosis	[39]
A satisfiability-based approach	[40]

DGBMO is suitable for large-sized UAV networks. The speed of convergence and the quality of solutions in the proposed algorithm is the best CPLEX and PBS approaches. *DGBMO* solve the sensor placement of nodes within a given topology to maximize fault diagnosis in network.

The rest of this paper is organized as follows. Section 2 presents the basic aspects and the characteristics of the gases. The GBMO algorithm is introduced in Section 3. In Section 4 Learning Automata is introduced. Section 5 discusses the distributed diagnosis approaches and develop DGBMO for the *MaxD* problem in network. Section 6 is devoted to the empirical results of proposed algorithm and its compression with the results obtained by ILP solver. The last section includes conclusions and future work.

2. Problem statement

Unmanned aerial vehicles (UAVs) are an important class of robotic applications. The UAV network is composed by n nodes (N_1, $N_2, \ldots, N_q$) and each node must communicate information (position and velocity) to neighboring nodes. *Hardware failures* and *software failures* could cause a node to transmit error values:

1. Physical redundancy
2. Analytical redundancy

We assigned to each node, *Ni*, a testing configuration and a communication configuration in this topology. A testing configuration is a set of sensors to monitor *Nj* (GPS sensor and a 3D laser) and a mathematical model, independently estimate *Nj*'s position. A communication configuration is the type of topology and cost.

In the proposed algorithm, we solve the ILP model which is introduced elsewhere [40]. Topology has been formulated and the ILP model has been solved like an optimization problem with a new discrete evolutionary algorithm. The proposed algorithm allocates nodes to slots such that the number of diagnosed nodes is maximized (*MaxD* problem).

Assume a problem with a topology including q empty slots and an equal number of nodes each with a specific testing and communication configuration is used. The ILP solver and the proposed algorithm allocate nodes to slots so that the number of diagnosed nodes is maximized.

$x_{ij} = 1$ if Ni occupies slot j; 0 otherwise
$mij = 1$ if node placed in slot i can monitor the node in j; 0 otherwise
$d_i = 1$ if the node placed in slot i is diagnosable; 0 otherwise
$pij = 1$ if a node Ni can communicate with Nj; 0 otherwise