

AN OPTIMIZED PROBABILITY DETECTION OF SPECTRUM IN COGNITIVE SENSOR NETWORK USING EVOLUTIONARY ALGORITHM

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Abstract

This project presents a semi-centralized stochastic election approach named Stochastic Election of Appropriate Range Cluster Heads (SEARCH) for design of heterogeneous wireless sensor networks. SEARCH assuring low time cost and optimal number cluster heads for each round. It is by boosting cluster head threshold of a node in a favourable position while deteriorating it otherwise, achieves an aggressive goal on prolonging the round of alive nodes surviving (notably stable period) as well as reducing energy consumption. In addition, we eliminate the unfavourable scenario that no cluster head emerges during some specific rounds, enhancing network performance.

1. Introduction

A cognitive sensor network is an intelligent sensor network that can be programmed and configured dynamically. Its transceiver is designed to use the best wireless channels in its vicinity. Such a network automatically detects available channels in wireless spectrum, then accordingly changes its transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band at one location. This process is a form of dynamic spectrum management. Cognitive sensor network is considered as a goal towards which a software-defined radio platform should evolve: a fully reconfigurable wireless transceiver which automatically adapts its communication parameters to network and user demands.

Although cognitive sensor network was initially thought of as a software-defined radio extension, most research work focuses on spectrum-sensing cognitive sensor network. Sensing-based Spectrum sharing: In sensing-based spectrum sharing cognitive sensor networks, cognitive sensor users first listen to the spectrum allocated to the licensed users to detect the state of the licensed users. Based on the detection results, cognitive sensor network users decide their transmission strategies. If the licensed users are not using the bands, cognitive radio users will transmit over those bands. If the licensed users are using the bands, cognitive radio users share the spectrum bands with the licensed users by restricting their transmit power.

Several research efforts are currently on-going around the world to introduce CR-related mechanisms at various OSI layers. A primary challenge being addressed is the identification of technical enablers for CR, i.e., theories, concepts, and practical algorithms to implement these mechanisms at a reasonable operational cost on flexible radio platforms. There have been many advances in the field of CR in recent years with respect to enabling environmental awareness and designing robust and flexible transmission techniques for hostile CR communication environments with varying channel conditions. Issues with efficient spectrum management, real

time implementation, CR security and applications, as well as regulatory and standardization aspects, all require significant attention for operation in cognitive networks. In response to the above, the CRAFT Workshop aims to gather researchers, engineers and practitioners both from academia and industry end users which aim to inspire the analysis and development of new solutions and realizations of the cognitive radio concept, and to present advanced flexible transmission techniques, platforms, and CR applications. The main focus of this workshop is on the practical implementation of the CR concept and the “shift-to-market” activity, including legal and economic aspects. The Workshop will welcome contributions presenting advances in various research areas of cognitive networking technologies and applications, specifically, but not exclusively related to the following topics

2. Related Work

Depending on the target applications, earlier studies in WSNs generally focus on either outdoor large-scale environments, where planned sensor deployment is difficult, or indoor small-scale monitoring zones, where sensor deployment mechanism is feasible and beneficial. For large-scale WSNs, several works have been proposed to address the energy conservation issue [2], [6], [1]. Given sufficient number of sensors randomly deployed over the monitoring field to ensure a certain degree of redundancy in sensing coverage, those proposals design node working schedules such that sensors can rotate between active and sleep modes. The objective of those proposed working schedules is to achieve energy conservation, while preserving reasonable sensing coverage and network connectivity.

For the monitoring environments where planned sensor deployment is possible, various static deployment strategies have been introduced to enhance the surveillance coverage [8], [4]. In this kind of research studies, one commonly considered metric is to minimize the number of sensors required to achieve a certain sensing coverage. Due to different sensor capabilities and manufacturing expenses, this metric is sometimes transformed into minimizing/optimizing the required total device cost for those deployed sensors, making this research subject more interesting yet challenging [5]. Such static deployment involves manual sensor placement/installation, and is incapable of dynamically repairing sensing voids in the presence of unexpected sensor failures.

Consequently, a number of research efforts have explored the movement assisted sensor deployment techniques by utilizing mobile sensors to enhance the sensing coverage after an initial random placement of sensors. With the motion facilities equipped at the sensing devices, sensors can move around to deploy themselves. Given any number of randomly placed sensors, the authors present a centralized force-guided algorithm, inspired by the disk packing theory and virtual force field concept from robotics, to establish motion paths for sensors. Assuming there exists a powerful cluster head, capable of communicating with all sensors and obtaining sensor locations, the proposed algorithm evaluates all attractive and repulsive forces and obtains the resultant force exerted on each sensor.

The computed resultant force then directs the sensor to move to a desired position. Also utilizing mobile sensors, the authors in [3] introduce a distributed sensor self deployment scheme. They suggest to firstly identify the coverage holes based on Voronoi diagram, and then propose three algorithms guide sensor movements toward the detected holes. Accurate Voronoi polygon constructions are not always possible to achieve, due to unevenly distributed sensors

with limited communication distances. Some optimization heuristic is needed to prevent sensors from moving too far and keep a reasonable number of total movements, further complicating the deployment computations. Furthermore, since the termination condition for the Voronoi-based deployment strategy is coverage, for a monitoring environment with sensor number much larger than necessary, unbalanced sensor distribution is likely to occur. As a result, the authors in [9] develop a scan-based movement-assisted sensor deployment (SMART) method to address the unbalanced problem.

Instead of tackling the deployment problem directly, SMART focuses on sensor load balancing by using 2D scanning and dimension exchanges to achieve a balanced network state. As claimed by the authors, SMART can operate on top of existing sensor deployment schemes, and produces good performance especially for unevenly distributed WSNs. The aforementioned movement-assisted sensor deployment techniques all consider homogeneous sensors. A more recent work [7] introduces the VorLag algorithm, which takes heterogeneous mobile sensors into the deployment considerations. The proposed VorLag solution enhances traditional Voronoi-based approach by incorporating Laguerre geometry to accommodate diversity in the sensing range/radius.

We observe that most previous works explore the sensor deployment problem only partially, leaving issues such as heterogeneous sensors and locally recovering sensing holes unaddressed. In practice, those closely-related deployment issues should be resolved as a complete protocol set to achieve an operative WSN with high detection capability. In light of this, we investigate the movement assisted sensor deployment subject by considering those deployment-related problems in a holistic manner. A CASA protocol suite is proposed to address the global sensor deployment scheme (EVFA-B) and sensing coverage recovery in the presence of sensor failures (SSOA). We summarize our unique contributions as follows. First, we develop the enhanced virtual forces algorithm with boundary forces (EVFAB) based on the concept of potential field and disk packing theory.

Though sharing similar idea of virtual forces with our EVFA-B deals with both the homogeneous and heterogeneous sensors, while only discusses the case of homogeneous sensors, where a global distance threshold value is adopted in determining whether an attractive or repulsive force should be applied on a sensor. In realistic settings, where varying sensing distances are common, the distance threshold should be selected on a node-pair basis, instead of being set globally [10]. In addition, since the observed environment is usually in a bounded area, our EVFA-B incorporates the boundary force as a kind of repulsive force from the boundaries to keep sensors staying inside the monitoring area.

Since the boundary force is considered as a type of repulsive force, we use the same value for w_r and w_b . No boundary force is modeled, and no specific design guidelines are available for determining suitable w_a and w_r (w_b) weight constants. The authors only suggest to select $w_r = w_a$. Through empirical evaluations, we discover that arbitrary settings do not always yield desirable sensing coverage. Motivated by the observations, we investigate and conjecture that good choices for w_a and w_r (w_b) greatly depend on sensor population and monitored area dimensions, while independent of sensing radius. Second, the SSOA is devised to provide network self-healing capability, which most previous sensor deployment protocols do not handle. Third, we observe that most existing works do not have a real-life testbed to demonstrate their proposed protocols/algorithms. In this work, we implement an automated MoNet, based on

embedded platforms, sensing components, communication modules and motion devices, to validate the proposed CASA protocol.

3. Differential Evolution Algorithm

In evolutionary computation, Differential Evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as metaheuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. Meta heuristics such as DE do not guarantee an optimal solution is ever found.

DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means DE does not require for the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time, etc.

DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand. In this way the optimization problem is treated as a black box that merely provides a measure of quality given a candidate solution and the gradient is therefore not needed.

A basic variant of the DE algorithm works by having a population of candidate solutions. These agents are moved around in the search-space by using simple mathematical formulae to combine the positions of existing agents from the population. If the new position of an agent is an improvement it is accepted and forms part of the population, otherwise the new position is simply discarded. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

4. Optimized Probability Detection Of Spectrum Using Evolutionary Algorithm

The internet has been evolved from internet of information toward the internet of things (IoT). Such evolution has further increase the spectrum load to handle the internet traffic which already in a very congested situation that yet to be solved. According to Cisco Canada, there will be estimated 50 billion devices connected to the internet by 2020 which mean that about 40 Zetta bytes of information will be running around the internet wirelessly. The concept behind IoT is to turn the everyday objects such as LED light tube, ceiling fan, air conditioner, kettle and water heater around us to become the smart objects which are aware of its environment through tracking, monitoring and are able to communicate their sensing data wirelessly over the internet with/without human intervention. Every smart objects are consider as a node that connect to each other through the gateway generally the access point to the cloud for further processing. To ensure a wider coverage, every node is design to connect to each other node in a distribute manner so that the sensing information can hop from one node to the other node until it reach the gateway successfully.

The smart computing enables the sensing information to talk to each other intelligently without human intervention. On the other side, human can retrieve the sensing information that is available on the cloud and control it through their handheld tablet, smart phone or computers that are connected to the internet. The IoT seems capable for bringing us to a prominent digital world, and hence a smart environment. The current spectrum is very congested with current

internet traffic load due to its static spectrum allocation scheme. The spectrum situation will get even worst with the exponential increase demand for transmission from the smart objects.

The differential evolution algorithms, had revolved into a powerful optimization algorithms and it had been successfully applied to many diverse real life applications. The simplicity to code with only few control parameters involved and effectiveness in solving numerous types of optimization problems including multi-objective, multi-modal, dynamic and constrained optimization problems had make DE to become one of the popular optimization.

DE is belonging to the group of evolutionary algorithms that operates in the same computational steps as employed by a standard evolutionary algorithm. Similarly, DE is a population based optimization tools that attacks the given problem by sampling the objective function at multiple and random chosen points. The simplicity and parallelizable characteristics of DE make it simple to use where only 4 basic strategies, which are initialization, mutation, crossover and selection.

5. Performance Analysis

The crossover value had been set at 0.95 and the scaled factor at 0.5. The various size of population from 5 to 150 with an increment of 5 each time was tested to determine the best population size to be sampled at the initialized process in order to achieve a better optimization result. The simulation shows that the population with size 30 outperforms the rest for the given spectrum sensing function in CSN. We can observe that the CSN reach above 0.93 with the population size of 45.

- || Detection probability is 0.921398
- || The energy utilization in milli joules is 7.533778

It is observed that as the population size continue to increase, the spectrum sensing function can reach a much higher optimal value as compare to the previous two graphs.

With size of population equals to 70, the optimal value can reach 0.94 and above. It's stable to maintain the detection optimal value at 0.9 and above. It is seen that by setting the size of populations 20 and above, it is reached the optimal sensing value 0.9 above which is a very satisfying condition to ensure the CSN operate in a stable condition. Overall, the simulation result had proved that DE can help the spectrum sensing function in CSN to achieve a better optimization result and hence increase its sensing performance.

The result is promising as the spectrum sensing is an important element in CSN for it to determine whether the spectrum is empty or not for further transmission. And the DE can help the spectrum sensing function to detect the incoming PU signal quickly so that the SU can immediately leave the spectrum. This feature can help the SU to use the licensed spectrum freely by minimizing the interference that it may cause to the PU.

NO	GENERATIONS	DETECTION PROBABILITY
1	5 to 30	0.866340
2	35 to 60	0.872547
3	65 to 90	0.888502
4	95 to 120	0.877500

5	125 to 150	0.902680
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Table .5.1 Numerical Results

6. Conclusion and Future Work

It is clear that the smart environment that complies of various smart objects which are connected wirelessly to the cloud will dominate the world in the near future. With the employment of CSN, the issue of spectrum congestion was solved significantly. With the assistance of DE optimization in probability detection of spectrum, the issue of interference was reduced. DE has been employed and it satisfies the optimized result and also probability detecting capability within a short period of time was improved. Energy Management was also achieved in smart environment.

In future, this work can be extended by using Real Coded Genetic Algorithm & Chatoic Genetic Algorithm.

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