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Ajith Abraham
Rafael Falcon
Mario Koeppen *Editors*

Computational Intelligence in Wireless Sensor Networks

Recent Advances and Future Challenges

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Janusz Kacprzyk, Polish Academy of Sciences, Warsaw, Poland
e-mail: kacprzyk@ibspan.waw.pl

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Editors
Ajith Abraham
Scientific Network for Innovation and Research Excellence
Machine Intelligence Research Labs (MIR Labs)
Auburn, WA
USA

Mario Koeppen
Department of Computer Science and Electronics
Graduate School of Creative Informatics
Kyushu Institute of Technology
Fukuoka
Japan

Rafael Falcon
Research and Engineering Division
Larus Technologies
Ottawa, ON
Canada

and

School of Electrical Engineering and Computer Science
University of Ottawa
Ottawa, ON
Canada

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Preface

Wireless Sensor Networks (WSNs) are rapidly becoming a technological cornerstone for modern societies. These collections of autonomous and distributed nodes capable of sensing, communication, processing, and even self-organization continue to earn notoriety as they serve as the backbone of emerging intelligent information-driven paradigms such as the *Internet of Things* [7, 12, 22], *Vehicular Clouds* [6, 19], or *Cyber-Physical Systems* [2, 4]. Over the last two decades, we have witnessed a plethora of developments related to theoretical innovations in WSNs that touch all aspects of their multilayered design, from more robust physical and medium access layers [23] to more efficient energy conservation [15, 18, 21] and self-organization protocols [5, 25]. The number of published surveys reporting successful WSN applications to dissimilar domains [1, 8–10, 20] is frankly overwhelming.

Computational Intelligence (CI) is a very active research discipline that encompasses a plethora of methodologies that draw inspiration from natural and social processes to model and solve a variety of challenging real-world problems [11, 13]. The appeal behind CI techniques revolves around the fact that they take into account the imprecise, vague, and uncertain knowledge that is often present in any realistic world model. Through the abstraction and simulation of intelligent systems such as bird flocks, fish schools, ant colonies, immune system cells, neural connections, and other highly parallel and distributed processes, the overhead imposed by the computational intractability of NP-hard optimization problems and, more recently, the emergence of Big Data [16], has been reasonably alleviated. The term CI is not indicative of a single methodology; rather, it describes a large umbrella under which several biologically and socially motivated techniques have emerged [11]. The CI field has outgrown its traditional foundations (centered around *artificial neural networks*, *fuzzy systems* and *evolutionary computation*) to embrace other related approaches that also pursue the same goals of tractability, robustness, and low solution cost [11, 13], including but not limited to: *rough sets*, *multi-valued logic*, *connectionist systems*, *swarm intelligence*, *artificial immune systems*, *granular computing*, *game theory*, *deep learning*, and the *hybridization* of the aforementioned systems.

CI techniques have much to offer to WSN in terms of the realization of periodical yet vital tasks such as *sensor node localization*, *data collection and aggregation*, *energy-aware routing/broadcasting*, and *sensor relocation* [14]. The interplay between both fields of study is growing in vitality and spills over other closely related areas such as *bio-inspired computing*, *robotics and vehicular systems*, thus crystallizing the foundations of an exciting multidisciplinary arena. *Bio-inspired networking* [3, 24] is a recently coined term that attempts to capture the impact of a large subset of CI methodologies to interconnected systems.

This volume is another initiative undertaken to emphasize the increasingly important role that CI methods are playing in solving a myriad of entangled WSN-related problems. The book serves as a guide for surveying several state-of-the art WSN scenarios in which CI approaches have been employed. The chapters in this volume do not offer an exhaustive picture of the rich landscape of CI-WSN applications given the breadth and depth of this interplay, with many problems rapidly arising as the pace of technology accelerates. The reader will find in this book how CI has contributed to solve a wide range of challenging problems, ranging from balancing the cost and accuracy of heterogeneous sensor deployments to recovering from real-time sensor failures to detecting attacks launched by malicious sensor nodes and enacting CI-based security schemes. Network managers, industry experts, academicians and practitioners alike (mostly in computer engineering, computer science, or applied mathematics) will benefit from the spectrum of successful applications reported in this volume. Senior undergraduate or graduate students may discover in this volume some problems well suited for their own research endeavors.

Volume Organization

Chapter 1 entitled "A Genetic Programming Approach to Cost-Sensitive Control in Wireless Sensor Networks" employs Genetic Programming (GP) to find suitable sensor control strategies that balance the accuracy of the measurements needed to monitor a certain region and the cost of powering these devices. In networks supporting multiple sensor types (a.k.a. heterogeneous WSNs), it is therefore desirable to develop cost-sensitive control algorithms that sample more expensive sensors only when necessary. The proposed solution has a twofold nature. First, a hierarchical method is proposed where GP solutions are sorted in a hierarchy of layers based on the cost of the sensors they use. Switching to the next more expensive layer takes place only if the prediction variance indicates uncertainty at lower layers. Second, the authors introduce non-hierarchical models that automatically select sensors based on both cost and accuracy. In experiments using a synthesized dataset and ten real datasets, the hierarchical method is shown to have significantly lower prediction costs than the non-hierarchical method.

Wireless Mesh Networks (WMNs) are a particular type of WSN whose topology can vary from a simple star network to an advanced multi-hop one. The main topological feature is that nodes are organized in a mesh topology, thus making WMNs a reliable infrastructure through the redundancy of multi-hop communications. In Chapter 2 "A Study on Performance of Hill Climbing Heuristic Method for Router Placement in Wireless Mesh Networks", the authors put forth an approach based on Hill Climbing (HC), a simple local search method, to quickly identify near-optimal router locations in a WMN so as to improve its Quality of Service (QoS) in terms of maximizing the network connectivity and client coverage. The ensuing bi-objective optimization problem is tackled via the HC heuristic method, whose performance is investigated under different distributions of client mesh nodes.

Chapter 3 titled "An Automated Irrigation System Based on a Low-Cost Microcontroller for Tomato Production in South India" introduces a practical result on a fuzzy logic-based irrigation controller for growing vegetables. The system consists of a feedback fuzzy logic controller that records key parameters with sensors, ZigbeeGPRS remote monitor, and a database. Based on the crop yield, the fuzzy logic controller acquires data from the sensors and applies fuzzy rules to determine a suitable irrigation time. A MaxMin inference engine and a Mamdani-type fuzzy inference system were adopted in order to make the best decision for each situation. The proposed system was developed and tested for the growth of tomato plants. It saves 50–60 % of the water utilization as well as the energy generation cost.

Chapter 4 "Artificial Neural Network Based Real-Time Urban Road Traffic State Estimation Framework" unveils a methodology that utilizes the existing cellular network infrastructure for road traffic data collection with a three-layer neural network model to estimate the complete link traffic state. The inputs to the neural network (NN) model include the probe vehicle's position, timestamps, and speeds. The framework integrates different modules that resort to different models in the process of traffic state estimation. Real A-GPS data gathered using A-GPS mobile phone on a moving vehicle on the set of chosen roads is used to evaluate the NN model. The trained NN is also used to estimate the road link speeds and compares them with ground truth speed (aggregate edge states) on a 10-min interval per hour. The estimation accuracy indicated that reliable link speed estimation can be generated and used to determine real-time urban road traffic conditions.

WSNs are subject to an ample range of potential attacks originated by malicious sensors. These attacks range from passive eavesdropping to active interfering and tampering of the communication. Chapter 5 "Attack Detection Using Evolutionary Computation" is concerned with the detection of such active attacks using the restricted capabilities of the sensor nodes. The underlying idea is that each sensor node is equipped with a simple intrusion detection system (IDS), hence an entire area can be monitored for malicious behavior in a distributed fashion. The automatic configuration of the IDS parameters is entrusted to *Multi-Objective Evolutionary Algorithms* (MOEAs) and illustrated via the selective forwarding attack and the delay attack. The proposed optimization framework provides Pareto front approximations consisting of different IDS settings with respect to three objectives, i.e., false positives, false negatives, and memory consumption. Furthermore, the authors discuss various attacker strategies and the robustness of the IDS settings found for a specific attacker strategy in cases where another attacker strategy is enacted.

Chapter 6 "Computational Intelligence Based Security in Wireless Sensor Networks: Technologies and Design Challenges" reviews the application of CI techniques to developing security schemes for WSNs. Fuzzy sets, rough sets, neurocomputing and evolutionary approaches are among the formalisms that have been proposed to enable WSNs with security features. There is broad uncharted territory when it comes to designing CI-based security systems for WSNs.

Wireless Visual Sensor Networks (WVSNs) are a type of WSNs that are heavily used for sensitive applications such as video surveillance and monitoring. To overcome the typical constraints of a WVSN in terms of its limited memory, energy, and bandwidth, Compressed Sensing (CS) techniques are brought into place with the aim of reconstructing sparse signals using very few measurements. Anomaly detection can then be accomplished in a more efficient manner using CS. Chapter 7 "Efficient Anomaly Detection System for Video Surveillance Application in WVSN with Particle Swarm Optimization" employs the popular Particle Swarm Optimization (PSO) metaheuristic algorithm to optimize the minimum number of compressed measurements and the routing of the information towards the destination. The proposed system is capable of detecting targets with fewer measurements and transmitting the required compressive measurements for reconstruction with less energy, thereby increasing the network lifetime.

Mobile robots are brought into a WSN to perform a wide range of tasks that optimize the WSN operation and extend its lifetime. One example of this is the replacement of damaged sensors with other functional, passive ones already deployed in the monitoring region. This problem has been recently studied under the name of *Robot-Assisted Sensor Relocation* (RASR) and cast as a combinatorial optimization problem. Chapter 8 entitled "Planning Robust Sensor Relocation Trajectories for a Mobile Robot with Evolutionary Multi-objective Optimization" extends the previous RASR formulation by actively considering the current energy levels of the participating passive sensors as well as the ideal locations for their deployment as additional decision objectives. This results in more robust sensor relocation trajectories to be pursued by the mobile robot. The authors explore six prominent MOEA implementations and discuss their performance with WSNs of varying sizes, inflicted damage levels, and passive sensor densities. They also tailor a recently proposed Risk Management Framework to proactively detect sensors that are at a high risk for failure and replace them before any network coverage is lost.

Future Challenges

The new generation of wireless networking involving the Internet of Things, Cyber Physical Systems etc., will result in *higher rate integrated communications*. Understanding and managing the complexity of such networks' bandwidth, capacity, security and Quality of Service (QoS) requirements will all be significant research challenges.

Currently we are also experiencing an *explosion of mobile data traffic*, characterized by the 4 V's Big Data vector: volume, velocity, variety, and veracity [16]. So, designing suitable frameworks to handle such Big Data in a wireless environment using appropriate Computational Intelligence tools will be a real challenge. Important aspects revolve around *real-time distributed control, processing and visualization* of these data streams in order to generate *actionable intelligence* that can better assist the decision-making process. A *risk-aware view* [17] of the WSN-monitored environment is not only beneficial but necessary in order to emphasize on the events of interest and declutter the operator's workspace.

We hope that the suite of technical contributions gathered in this book help drive further momentum into many theoretical and practical aspects of the wonderful synergy between CI methods and the WSN realm. Enjoy the reading!

Auburn, USA — Ajith Abraham
Ottawa, Canada — Rafael Falcon
Kyushu, Japan — Mario Koeppen
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Contents

A Genetic Programming Approach to Cost-Sensitive Control in Wireless Sensor Networks

Afsoon Yousefi Zowj, Josh C. Bongard and Christian Skalka

Abstract In some wireless sensor network applications, multiple sensors can be used to measure the same variable, while differing in their sampling *cost*, for example in their power requirements. This raises the problem of automatically controlling heterogeneous sensor suites in wireless sensor network applications, in a manner that balances cost and accuracy of sensors. We apply genetic programming (GP) to this problem, considering two basic approaches. First, we construct a hierarchy of models, where increasing levels in the hierarchy use sensors of increasing cost. If a model that polls low cost sensors exhibits too much prediction uncertainty, the burden of prediction is automatically transferred to a higher level model using more expensive sensors. Second, we train models with cost as an optimization objective, called non-hierarchical models, that use conditionals to automatically select sensors based on both cost and accuracy. We compare these approaches in a setting where the available budget for sampling is considered to remain constant, and in a setting where the system is sensitive to a fluctuating budget, for example available battery power. We show that in both settings, for increasingly challenging datasets, hierarchical models makes predictions with equivalent accuracy yet lower cost than non-hierarchical models.

1 Introduction

Wireless Sensor Networks (WSNs) have revolutionized environmental monitoring by combining low cost with flexibility in sensor capabilities [31]. They have been used in diverse environmental monitoring applications and continue to be adapted in new fields. Because WSNs are often, even typically, deployed in remote locations, and

A.Y. Zowj (✉) · J.C. Bongard · C. Skalka
Department of Computer Science, University of Vermont, Burlington, VT, USA
e-mail: ayousef1@uvm.edu

J.C. Bongard
e-mail: jbongard@uvm.edu

C. Skalka
e-mail: ceskalka@uvm.edu

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thus rely on combinations of battery power and energy harvesting, a major challenge in WSN design is to minimize system power consumption.

Minimizing power consumption can be accomplished in a variety of ways, in particular by adapting sensor control strategies that optimize the balance between measurement accuracy and the cost of powering sensors [30]. In this paper, we propose new sensor control algorithms for WSNs with heterogeneous sensor suites that balance cost and accuracy, obtained using genetic programming (GP) techniques.

By "heterogeneous sensor suite", we mean WSNs equipped with multiple types of sensors for prediction of the same phenomena. Each of these sensors is characterized by its accuracy in relation to the phenomena, and a cost of use which is often measured by its power consumption. Such systems support multi-modal sensor fusion, a well-studied technique where data from multiple sensor modalities (types) is combined to predict a single variable [30]. The contribution of our work is a consideration of cost in multi-modal sensor fusion, and the development and testing of associated control algorithms. These algorithms will call upon particular sensors only when needed, and otherwise rely on the cheapest available sensors at any given time. Our problem is distinguished from adaptive sampling [30] in that the latter is concerned with optimally modulating sampling frequency of a given sensor, not choosing between a suite of possible sensors.

While various multi-modal sensor fusion applications exist, we are especially interested in the Snowcloud system which combines snow density telemetry with snow depth and air temperature sensors to predict areal snow water equivalent (SWE) [24]. We envision extending Snowcloud to incorporate ground based light detection and ranging (LIDAR) scanning [5] to be used for SWE estimation as part of its sensor suite. However, while LIDAR yields more accurate data than existing Snowcloud telemetry, it does so at significant additional power cost. Thus, the challenge is to commit these resources only at optimal times. It is also a refinement of multi-modal sensor fusion, since we are mainly interested in settings where available data gathering techniques differ in accuracy, with less accurate sensors being cheaper than more accurate ones.

A fundamental component of our approach is the use of prediction *uncertainty* to drive sensor usage. We propose a scheme whereby predictions are attempted using lower-cost sensors at first. If uncertainty is below an acceptable threshold, then the prediction is used. Otherwise we switch to higher-cost sensors, make a new prediction based on those inputs, evaluate uncertainty again, and continue to move the burden of prediction to more accurate and costly sensors as needed. This scheme is discussed in detail in Sect. 2.4 and described graphically in Fig. 2. Note that while the Snowcloud system is an intended application of this scheme, it can be generalized to any WSN application using heterogeneous sensor suites comprising sensors with varying cost and accuracy.

To quantify uncertainty we are aided by machine learning ensemble methods—we use entropy in ensemble predictions as a proxy for uncertainty [23]. To obtain predictive models themselves, in this work we use genetic programming (GP) [14]. This is largely due to characteristics of our intended application space. Previous work has demonstrated that the relationships between snow cover and the topographic and meteorological factors that influence it include non-linearities [26], while the spatial distribution of SWE is nonlinear because it is influenced simultaneously by various forcing effects [27]. Nonlinear predictors are therefore desirable. Furthermore, recent results [7] show that GP has advantages over other approaches (such as decision trees) due to associated techniques for preventing overfitting, e.g. treating model size minimization as an objective [12]. Although C4.5 only supports classification, sufficiently fine classification granularity can achieve competitive performance on regression problems, and this approach is popular in the environmental science community [7]. Finally, GP is appealing due to its white-box nature: it can potentially provide physical insights into modeled phenomena.

An alternative approach to our problem is to not rely on external measures of entropy to switch between sensors, but to treat cost as an additional objective in a multi-objective optimization problem. We explore this option in our work, in direct comparison to the hierarchical approach. However, due to the "curse of dimensionality", adding another optimization dimension may have deleterious effects on prediction performance, especially since selection for size to avoid overfitting already imposes a multi-objective optimization regime [6]. We therefore hypothesize that a hierarchical approach will outperform a non-hierarchical approach in settings with multiple sensors of differing predictive abilities, and we explore this comparison in our experiments.

In our initial comparison of these two approaches—hierarchical and non-hierarchical—our regime is not concerned with the available budget. However, in real deployments, budget levels can have significant impacts on what sensors are chosen. For example, if battery levels are low, expensive sensors should probably be avoided regardless of prediction uncertainty, both to reduce system downtime and sensor noise. Therefore, we also consider a comparison of the hierarchical and non-hierarchical approaches in a setting where models are sensitive to dynamic budget fluctuations. As for the basic setting, we hypothesize that the hierarchical approach will perform better than the non-hierarchical.

1.1 Related Work

Previous work on adaptive sampling [30] has aimed to reduce sampling rates in Resource Constrained Sensor Systems (RCSS) applications to balance sensor cost and accuracy. In particular, Alippi et al. [4] have tried to find the optimal adaptive frequency of sampling for avalanche monitoring. It has further been claimed that compressed sensing—sending aggregated data instead of raw data—performs better in conjunction with reducing sampling rates, rather than just reducing the sampling rate alone [17]. A variety of methods for compressed sensing [8] have been proposed. Although these methods have achieved cost reduction in monitoring, they are not applicable to our problem since we intend not to change the rate of sampling of one sensor type, but rather to reduce sampling cost by switching between available sensors of different type and accuracy.

Another line of work focuses on finding the optimal location for sensors in distributed deployments, in order to maximize accuracy while minimizing deployment densities. Krause et al. [15] have used a probabilistic method to predict the communication cost for a given deployment topology. Papadimitriou et al. [19] have employed GP and a Bayesian statistical method to minimize entropy over a set of sensor locations. In contrast, our work is concerned with reducing the cost of sampling from an available set of sensors at any given time, not with reducing the densities of sensor topologies.

In work on so-called multi-modal sensor fusion, data from multiple sensors in a potentially heterogeneous suite are aggregated to monitor a specific measurement application [9, 28]. This method has been widely used, for example in visual monitoring [18, 20] and target tracking [21, 25]. Data fusion focuses on sensor applications that need to compute the correlation between multiple sensor modules and cannot be measured by a single sensor. However, these works do not consider the cost of using different sensors, or minimizing cost.

Cost sensitive multi-modal sensor fusion methods have been developed to balance cost against accuracy, with an eye towards providing fault tolerance [13]. However, we are not concerned with fault tolerance, but strictly between selecting sensors from heterogeneous suites. Willett et al. [30] use a small number of sensors to send their readings to a fusion center, and based on the correlation among the sensed data, the fusion center decides which additional sensors should be activated. The same concept has also been tried in a distributed fashion [16]. However, sensing costs in these cases are a function of the number of sensors sampled, not their type.

Perhaps most related to our work is that of Wang et al. [29]. They propose a method to find the optimal set of sensors to be polled, using a hybrid tree, where non-leaf nodes act as a decision tree and leaves are standard regression models using a subset of sensors. However, these trees support decision making based on external constraints, i.e., which sensors to use depending on an organization's goals and resources. In contrast, our models are intended to support automated sensor control in WSNs during deployments.

Outside of the adaptive sampling and sensor fusion fields, multi-objective optimization has been used for cost-sensitive modeling. For example Kim [12] sets error as one objective and tree size as another, as we do here. Zhao [32] sets the false negative rate and false positive rate as the two objectives. However, these works do not consider the hierarchical approach that we do.

1.2 Organization of the Chapter

The remaining text is organized as follows. In Sect. 2 we formalize our basic problem description, and explain how hierarchical and non-hierarchical models are constructed. In Sect. 3 we describe the experiments we perform to compare these two approaches, and the quantitative results from those experiments. In Sect. 4 we describe an extension where dynamically changing budget information can be taken