A Survey of Machine Learning in Wireless Sensor Netoworks

- From Networking and Application Perspectives -

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***Abstract*—Wireless Sensor Networks (WSNs) are used to collect data from and make inferences about the environments or objects that they are sensing. These sensors are usually characterized by limited communication capabilities due to energy and bandwidth constraints. As a result, WSNs have inspired resurgence in research on machine learning methodologies with the objective of overcoming the physical constraints of sensors. In this paper, machine learning methods that have been applied in WSNs to solve some networking and application problems are surveyed. Fundamental limits of learning algorithms will be addressed and future machine learning research direction are highlighted.**

***Keywords*—WSN, machine learning**

I. INTRODUCTION

WSNs have attracted considerable amount of attention in recent years. Research in WSNs area has focused on two separate aspects of such networks, namely networking issues, such as capacity, delay, and routing strategies; and application issues [1]. This paper will survey the machine learning methods used in WSNs from both aspects.

WSNs technology has a promising future in many application domains. They have been used as battlefield surveillance instruments in military applications, building structural monitoring in construction industry, patient bio-signal monitoring in health-care industry and etc. With the rapid progress in MEMS technology, it is possible to deploy large-scale sensors in the field in the near future [2]. However, large-scale sensor network also unavoidably introduce large amount of data in WSNs to be processed, transmitted and received. Transmitting all data back to a base station for processing and making inferences is merely impossible due to the sensor limited energy and bandwidth constraints. Thus, there is a need for applying machine learning methods in WSN. This strategy could significantly reduce the amount of data communications and truly utilize the distributive characteristic of WSNs.

This paper will survey machine learning in WSN application from two perspectives, namely the *network associated issue* and *application associated issue*. In the network associated issue, different machine learning algorithms applied in WSNs to improve network performance will be discussed. In application associated issue, machine learning methods that have been used for information processing in WSNs will be summarized. The rest of paper is organized as follows. Section II presents different machine learning algorithms applied in WSNs to solve some specific network associated problems, such as energy-aware communication, node localization, resource allocation and etc. Section III surveys application of machine learning in WSNs information processing, including object or event identification, pattern recognition and etc. Section IV discusses the future trend of machine learning in WSNs. Section V summarizes the survey result and concludes the work.

II. MACHINE LEARNING FOR NETWORKING

A. Energy-aware Communications

One of the major objectives of many WSN research works is to improve or optimize the performance of the entire network in terms of energy-conservation and network lifetime. Most of the research activities focus on the design of efficient routing protocol at the network layer (e.g., [3]-[5]), selection of low-power modulation scheme at the physical layer (e.g., [6]) or adoption of power-saving modal of operation at data link layer (e.g., [7]) to achieve energy-awareness in WSNs. However, there is a noticeable trend that machine learning techniques have been applied to explore energy-aware communication in WSNs.

Many of the WSN applications rely heavily on fast, efficient and reliable data communications. However, WSN communication links are inherently unreliable due to its loosely-coupled nature. Therefore, communication protocols employ *situation-aware adaptation* to identify healthy and energy-efficient routes. The authors of [8] introduce a supervised learning approach for routing optimization in WSNs. The algorithm uses machine learning techniques to improve the situation-awareness in order to optimize

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communications. Essentially, it uses machine learning to automatically discover the correlations between input features (e.g., node-level and network-level metrics, such as buffer occupancies, packet length, node residual energy) and output (e.g., link quality, optimal route).

The machine learning process of [8] is carried out in four steps, namely 1) Feature selection and output labeling, 2) Sample collection, 3) Offline training and 4) Online classification.

Feature selection is the process of choosing the most appropriate feature vector that best represents the problem at hand. In the context of WSN, feature vector could consist of network parameters such as fast fading, slow fading, traffic pattern, signal strength and etc. Output labeling is the process of classifying outputs using domain knowledge.

Sample collection is the process of collecting data for training purpose. A backend server is also used in the system as a data collector and processor. This is known as centralized learning in terms of architecture. However, in many real-life applications, deploying a backend sever in WSNs is not efficient or even impossible, thus a decentralized/distributed learning architecture is sometimes preferred.

Offline training is the actual learning process. The authors of [8] evaluates two classifiers – decision tree (C4.5 algorithm) and rule-based learner. These learning algorithms have a rich history; they may not be the best solution for WSNs as they take a centralized approach and have no consideration of resource constraints. Learning overhead is only considered in the online classification phase because offline training is done by a resource-rich backend server. In many WSN applications, learning overhead is also present in the training phase, thus a more distributed, efficient and scalable learning algorithm minimizes the training overhead need to be considered.

The authors of [9] introduce a near-optimal reinforcement learning framework for energy-aware sensor communications. The problem is formulated as average throughput maximization per total consumed energy in sensor communications. A near-optimal transmission strategy was obtained based on a reinforcement learning framework. This strategy chooses the optimal modulation level and transmission power while adapts to the incoming traffic rate, buffer and channel conditions. The motivation of using the machine learning approach is that many solutions of channel throughput maximization requires the state transition probability, which may be hard to obtain. Machine learning, however, could obtain a near-optimal transmission policy in point-to-point scenario, without deriving a complex communication model.

The authors of [10] and [11] explore fuzzy logic based sensor communications in WSN. Existing energy-aware routing protocols use crisp metrics for making routing decisions. It has the disadvantage of not being easily adaptive to changes in sensor types because metrics vary with the type of sensors as well as application scenarios. This does not support the design of isotropic sensors (sensor can be deployed for multiple purposes). Fuzzy logic, on the other hand, allows imprecise data and using heuristic human reasoning to obtain output.

The author of [11] defines a fuzzy routine to determine the desired value of cost of a link between two sensor nodes with the objective of maximizing the network lifetime. Transmission energy, residual energy, energy consumption rate, queue size, distance from gateway are selected as input variables and link cost is the interested output fuzzy set. Defuzzification is carried out to obtain a crispy value of the link cost. Instead of using fuzzy logic to obtain a routing decision (finding the link cost), the authors of [10] utilize a fuzzy logic controller at each sensor node to determine its capability to transfer data packets in the WSN. The inputs of the fuzzy controller are node residual energy, type flag of data packet and etc. Sensor nodes will either participate or be inactive in data communications (forwarding, bridging and etc.) based on the crisp output of the fuzzy controller.

B. Optimal Node Deployment and Localization

Sensor node deployment and localization are two interrelated issues in WSNs. With different node deployment strategies, the localization algorithms could also be totally different. For example, sensor nodes deployed manually may be localized using a walking GPS method. However, the GPS method would be too costly and time-consuming if sensor nodes are to be deployed randomly in large scale. In this case, parameters such as signal strengths, message delivering speeds, relative orientation can be used to estimate the sensor location using machine learning techniques.

Deployment

The author of [12] developed a fuzzy deployment scheme for WSN surveillance application. The assumption for most of the node deployment is that the environment is homogeneous. The effect of terrain profile (such as obstacles, altitude, criticality of certain area and etc.) has been ignored under such assumption. Nevertheless, these profiles may be important in deploying a node; in this case, a more critical area under surveillance might need more sensors. The deployment problem in [12] has been formulated as selecting an optimal node spread pattern to achieve maximum information gain. First, the area of interest is divided into sub-areas, each of which has its own terrain profile. Second, based on the terrain profile, a fuzzy logic system is used to compute the number of nodes in each sub-area. Simulation studies show that the fuzzy deployment scheme could achieve a higher coverage ratio and information gain in the surveillance system.

The author of [13] introduces a fuzzy optimization algorithm to efficiently adjust sensor placements after an initial random deployment. The basic approach in [13] resembles that of [12], both employ fuzzy logic to obtain an optimal spread of nodes in the field to achieve higher information gain. In addition to fuzzy systems, method in [13] also assumes that nodes have certain mobility - one could adjust its position based on some global or local interaction. A fuzzy re-deployment (or adjusting) scheme is carried out only after the nodes have been randomly deployed in the field.

The fuzzy deployment scheme introduced in [12] and [13] has a very limited application, such as field surveillance. The authors of [14] introduce a general near-optimal sensor placement model which maximize information gain while minimizes communication cost regardless of applications. This model is not only applicable to surveillance WSNs but also other WSNs applications as well.

Localization

Location information is an important parameter in both networking and application domains of WSN. Accurate location estimation is a basic prerequisite for energy-aware routing and sensor event localization and reporting. There are generally two approaches to tackle the localization problem in WSN, namely hardware-based and probabilistic estimation-based approaches.

The authors of [15] propose using fuzzy logic to do away with strict probabilistic rules and set up heuristic fuzzy rules for localization in WSN. The algorithm uses a grid based approach in which a node's location is represented by its confidence level that it stands at a certain point in this grid. The confidence level is computed based on the fuzzy logic system and the input variables of the fuzzy system are sensor measurements such as signal strength, time difference of arrival and etc.

The authors of [16] adopt an evolutionary approach, namely a micro genetic algorithm and its extension to enhance the precision of existing localization methods. This is not a localization algorithm rather a post-optimizer for any other localization algorithms. It makes use of two genetic operators, namely the mutation and crossover operators, aiming at opportunistic decreases in the objective values obtained to mutate out current node location estimation, or crossover points for any pairs of existing chromosomes over successive generations for localization. Simulation results indicate that this post-optimizer improves the precision of various localization algorithms from 11.0% to 18.6% on average.

C. Resource Allocation and Task Scheduling

Resource allocation and task scheduling are the major research challenges in the field of WSNs in terms of system-wise interaction. Unlike energy-aware communication or optimal deployment and localization which optimizes a particular objective function of a node, optimization problems formulated under these two scenarios are from a more global perspective, namely, how a group of sensor nodes could be managed and scheduled to achieve some system objectives, such as a tradeoff between network lifetime and information gain.

The authors of [17] explore three machine learning algorithms for task scheduling in radar sensor networks and compares the simulation results. The algorithms used are fuzzy Lyapunov synthesis, genetic algorithms and neural networks. The simulation results show that GA outperforms the others. This study was initially carried out to address the radar scheduling problem, however, the result could be immediately applicable to WSN due to similar system architecture setting (WSNs and radar sensor network).

The authors of [18] and [19] propose an adaptive distributed resource allocation scheme which specifies relatively simple local action to be performed by individual nodes in a WSN for management of system modes. Each node adapts its operation over time in response to the status and feedback of its neighboring nodes. Although the adaptive operation is defined locally, optimal global behavior results from these local interactions. The scheme has been studied in two separate application scenarios, namely an acoustic WSN for field surveillance and camera network for traffic monitoring. Simulation results show that it provides a good tradeoff between performance objectives such as target tracking accuracy, coverage area, and network lifetime.

The authors of [20] introduce a novel fuzzy approach for cluster head election in WSN. Strictly speaking, cluster head assigning is a step in hierarchical routing in WSN. However, it could also be viewed as a resource allocation scheme in WSN as assigning the role of cluster head to nodes is functionally equivalent to allocating resources to the node. The fuzzy system in this research takes in three parameters – node energy, node concentration and centrality with respect to the entire cluster. The output is a decision of which node shall become the cluster head. The scheme allows an even energy consumption across the network thus improving the overall network lifetime.

III. MACHINE LEARNING FOR INFORMATION PROCESSING

A. Background

Information processing in WSNs has three major steps namely pre-processing, data aggregation and inference. Pre-processing is the first step of information processing. It includes simple actions performed on raw data such as signal conditioning (smoothing, scaling and etc.), noise filtering and etc. Data aggregation is the process of aggregating data to the fusion centre or inference centre in WSN. Inference is a process of using machine learning techniques to extract hidden information out of the aggregated data. Most of current researches focus on applying machine learning algorithms for making inference (step three of information processing in WSNs), such as classifying a moving object in a surveillance WSN based on data gathered by the sensors, abnormal environmental event identification in an environment monitoring WSN. These applications will be surveyed in this paper. However, there is a general belief that machine learning techniques could and should be applied as an integrated optimal information processing strategy into all three steps.

B. *Information Processing*

In [21] - [24], a series of issues(data acquisition and pre-processing, neural networks implementation and application) of applying wavelet neural networks for information processing in WSNs have been discussed. The information processing algorithms in WSNs are mainly modified regression techniques from the field of multidimensional data series analysis in other fields, such as nearest neighbor search, principal component analysis and etc. These researches demonstrate that some of the algorithms well developed within the neural network domain over past 30 years are well suited for information processing requirements imposed by WSNs, such as parallel distributed computation, distributed data storage, robust data acquisition and querying, and most importantly, data set classification. Two algorithms, namely ART (adaptive resonance theory) and FuzzyART have been proposed. These unsupervised learning algorithms are performed on the cluster heads of WSNs, this approach only computes sub-global classification, and thus presents a limitation when a single global result is desired.

C. *Target tracking in WSN*

In [25], a neural network-aided unscented Kalman filter for tracking maneuvering objects in an acoustic surveillance WSN is presented. A BP (back propagation) neural network is used to correct the errors in modeling a maneuverable object in WSN, and the nonlinear inferring process is accomplished by a normal UKF (unscented Kalman filter). The inputs of the BP neural network are the parameters which have direct influence over the tracking error, and the output is the estimated bias between the UKF's output and the true state.

In [26], algorithms from mobile robot field are brought into WSNs. It introduces an extended SLAM (simultaneous localization and mapping) algorithm to solve the problem of tracking a target in WSNs. The proposed solution, known as LaSLAT (simultaneous localization and tracking), is a Bayesian filter that provides online probabilistic estimates of sensor locations and target tracks. One of the direct benefits of using the Bayesian filter is that sensor measurement noise is automatically averaged out as more measurements become available, thus improving the localization and tracking accuracy in the high traffic area.

Most of the multi-target tracking algorithms are based on joint probabilistic data association. The authors of [27] argue that it is difficult to apply the solution to the problem (due to the curse of dimensionality) when the number of target varies dramatically. It introduces an algorithm known as ADMAN (Algorithm for Detection of Multi-targets in Wireless Acoustic Sensor Network) which is able to cope with any time variation in the number of targets without being affected by the dimensionality curse.

D. *Event Classification and Identification of Target Class*

In many surveillance WSN applications, a detected target not only should be tracked in the field, but also need to be classified according to its identity. Likewise, an abnormal environmental condition shall be precisely identified in an environment monitoring WSN. These are the classical machine learning problems associated with statistic pattern recognition.

There are many literatures in the field of classification. These researches use either spectral or wavelet techniques to extract the feature vector, which represents different targets, in the frequency domain. In [28], a time-domain feature extraction method, known as TESPAR (Time Encoded Signal Processing and Recognition) is introduced. It is used to produce fixed size of feature matrices from sensor measurements (acoustic sensor waveform). A neural network is then used to classify the targets based on the matrices produced.

The author of [29] demonstrate that the same machine learning algorithms used in classifying objects in an surveillance WSN could also be applied in BSN (body sensor network) to analyze and classify human motion context. Body sensor nodes are equipped with accelerometer; human motion will cause the waveform of the accelerometer to change accordingly. This change in waveform captured by sensor nodes is then analyzed by PCA (principal component analysis) and SVM (Support Vector Machine) method for clustering and classification.

IV. FUTURE TREND OF MACHINE LEARNING IN WSN

Machine learning based information processing in WSN is at its entering stage, as compared to traditional machine learning and WSN. Currently, researches mainly focus on applying machine learning techniques to solve a particular problem in WSN. Different researchers will have different assumptions, application scenarios and preferences in applying machine learning algorithms. These differences represent a major challenge in allowing researchers to build upon each other's work so that research results will accumulate in the community. Thus, a common architecture across the WSN machine learning community would be necessary.

The learning architecture in WSNs is surveyed in [1] . This paper points out the application issues and research challenges of distributed learning framework in WSNs. It also sets out two paths towards a unified learning approach – distributed learning in WSNs with a fusion centre, where the focus is on how learning is effected when communication constraints limit access to training data; and distributed learning in WSN with in-network processing, where the focus is on how inter-sensor communications and local processing may be exploited to enable communication-efficient collaborative learning. Figure 1 depicts the two models. As a result, Future researches will unavoidably focus on the distributed learning framework in

WSN rather than applying machine learning algorithms to tackle a single problem and aggregate the results.

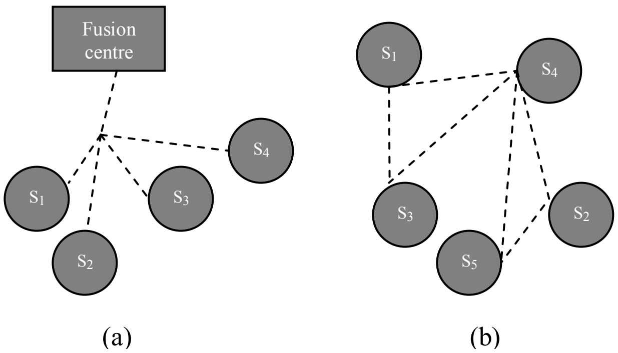

Fig.1. (a) A parallel WSN with fusion centre. (b) An Ad hoc WSN with in-network processing.

V. CONCLUSIONS

This article surveys the machine learning techniques applied in WSN from both networking and application perspectives. Machine learning techniques have been applied in solving problems such as energy-aware communication, optimal sensor deployment and localization, resource allocation and task scheduling in WSNs. In application domain, machine learning methods are mainly used in information processing such as data conditioning, machine inference and etc.

REFERENCES

[1] S. R. K. Joel B. Predd, and H. Vincent Poor, "Distributed Learning in Wireless Sensor Networks - application issues and the problem of distributed inference," *IEEE Signal Processing Magazine*, 2006.

[2] D. E. D. Culler, and M. Srivastava, "Overview of sensor networks," *IEEE Computer*, pp. 41-49, 2004.

[3] R. G. C. Intanagonwiwat, and D. Estrin, "Directed Diffusion: A Scalable and Robust Communication Paradigm for Sensor Networks," presented at ACM MobiCom, Boston, MA, 2000.

[4] A. C. W. R. Heinzelman, and H. Balakrishnan,, "Energy-Efficient Communication Protocol for Wireless Microsensor Networks," presented at IEEE Proc. Hawaii Int'l. Conf. Sys. Sci., 2000.

[5] K. Sohrabi et al., "Protocols for Self-Organization of a Wireless Sensor Network," presented at IEEE Pers. Commun., 2000, Oct.

[6] I. E. C. Chien, and C. McConaghy, "Low-Power Direct-Sequence Spread-Spectrum Modem Architecture For Distributed Wireless Sensor Networks," presented at ISLPED Huntington Beach, CA, 2001.

[7] A. S. a. A. Chandrakasan, "Dynamic Power Management in Wireless Sensor Networks," presented at IEEE Design Test Comp, 2001.

[8] M. M. Yong Wang, and Li-Shiuan Peh, "A Supervised Learning Approach for Routing Optimizations in Wireless Sensor Networks," 2006.

[9] C. P. a. K. J. R. Liu, "Near-Optimal Reinforcement Learning Framework for Energy-Aware Sensor Communications," *Communication*, 2005.

[10] R. C. a. V. V. T.Srinivasan, "A Fuzzy, Energy-Efficient Scheme for Data Centric Multipath Routing in Wireless Sensor Networks," 2006.

[11] T. H. Mariam Yusuf, "Energy-Aware Fuzzy Routing for Wireless Sensor Networks," presented at International Conference on Emerging Technology, 2005.

[12] Q. L. Liang Zhao, "Fuzzy deployment for wireless sensor networks," presented at Computational Intelligence For Homeland Security and Personal Saftey, 2005.

[13] Q. L. Haining Shu, "Fuzzy Optimization for Distributed Sensor Deployment," presented at WCNC, 2005.

[14] C. G. Andreas Krause, Anupam Gupta and Jon Kleinberg, "Near-optimal sensor placement," presented at IPSN, Nashville, Tennessee, USA, 2006.

[15] J. L. a. S. J. Avinash Gopal Dharne, "Using Fuzzy Logic for Localization in Mobile Sensor Networks: Simulations and Experiments," presented at American Control Conference, 2006.

[16] K.-Y. C. a. K.-S. L. Vincent Tam, "A Descend-Based Evolutionary Approach to Enhance Position Estimation in Wireless Sensor Networks," presented at ICTAI, 2006.

[17] J. d. J. Wilbert van Norden, Fok Bolderheij, Leon Rothkrantz, "Intelligent Task Scheduling in Sensor Networks," presented at international Conference on Information Fusion, 2005.

[18] H. B. L. Mao Ching Foo, Yulian Zeng, Vinh The Lam, Rodney Teo, Gee Wah Ng, "Impact of Distributed Resource Allocation in Sensor Networks," 2005.

[19] H. B. L. Mao Ching Foo, Yulian Zeng, Vinh The Lam, "An adaptive distributed resource allocation scheme for sensor networks," presented at LNCS, 2006.

[20] D. R. Indranil Gupta, Srinivas Sampalli, "Cluster-head Election using Fuzzy Logic for Wireless Sensor Networks," presented at CNSR, 2005.

[21] D. D. Andrea Kulakov, "Intelligent Data Acquisition and Processing Using Wavelet Neural-Networks," presented at Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Application, 2005.

[22] D. D. Andrea Kulakov, Georgi Stojanov, "Learning patterns in wireless sensor networks based on wavelet neuralnetworks," presented at ICPADS, 2005.

[23] D. D. Andrea Kulakov, Goran Trajkovski, "Implementing artificial neural-networks in wireless sensor networks," 2005.

[24] D. D. Andrea Kulakov, "Distributed data processing in wireless sensor networks based on artificial neural-networks algorithms," presented at ISCC, 2005.

[25] S.-L. D. Zhi-Jun Yu, Jian-Ming Wei, Tao Xing, Hai-Tao Liu, "Neural Network Aided Unscented Kalman Filter for Maneuvering Target Tracking in Distributed Acoustic Sensor Networks," presented at ICCTA, 2007.

[26] A. R. a. J. B. Christopher Taylor, "Simultaneous Localization, Calibration, and Tracking in an ad Hoc Sensor Network," presented at ISPN, 2006.

[27] J. L. Jaechan Lim, Sangjin Hong, Peom Park, "Algorithm for Detection with Localization of Multi-targets in Wireless Acoustic Sensor Networks," presented at ICTAI, 2006.

[28] J. A. Georgios Mazarakis, "Lightweight Time Encoded Signal Processing for Vehicle Recognition in Sensor Networks," 2006.

[29] N. J. K. Joo Hyun Hong, Eun Jong Cha, Tae Soo Lee, "Classification Technique of Human Motion Context based on Wireless Sensor Network," 2005.