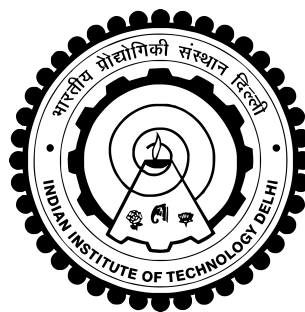


ENERGY-EFFICIENT SENSING STRATEGIES FOR WIRELESS SENSOR NETWORK-BASED IOT APPLICATIONS

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ENERGY-EFFICIENT SENSING STRATEGIES FOR WIRELESS SENSOR NETWORK-BASED IOT APPLICATIONS

by

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Submitted

*in fulfillment of the requirements of the degree of Doctor of Philosophy
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DEDICATED TO
my beloved parents and husband.

Certificate

This is to certify that the dissertation entitled **Energy-Efficient Sensing Strategies For Wireless Sensor Network-based IoT Applications**, submitted by **Ms. Vini Gupta**, a Research Scholar, in the *Department of Electrical Engineering, Indian Institute of Technology Delhi, New Delhi, India*, for the award of the degree of **Doctor of Philosophy**, is a record of an original research work carried out by her under my supervision and guidance. The dissertation fulfills all requirements as per the regulations of this Institute and in my opinion has reached the standard needed for submission. Neither this dissertation nor any part of it has been submitted for any degree or academic award elsewhere.

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Vini Gupta

Abstract

With the advent of the Internet of Things (IoT), the quantum of data produced by the IoT devices poses serious challenges on its storage, communication, computation, security, scalability, and system's energy sustainability. To address these challenges, this dissertation aims at providing frameworks for energy-efficient optimized sensing at the node-level and network-level in wireless sensor network (WSN)-assisted IoT applications. Correlation inherent in the monitoring process allows performing sparse/parsimonious sensing without compromising the sensing quality, thereby saving energy. Further, these under-sampled measurements are utilized to estimate the process signal and generate its heat-map across the entire WSN field.

In the first part of the dissertation, a novel centralized adaptive sensor selection framework to improve the durability of a densely deployed WSN monitoring a spatio-temporal process is developed. Owing to the correlation inherent in the process, the idea of turning-ON/activating a few sensor nodes (SNs) selected by jointly optimizing the sensing quality and energy efficiency of the WSN is proposed. A feedback mechanism is developed to adapt the size of the active SNs set as per the estimated variations of the underlying process. Further, a joint Principal Component Analysis-Sparse Bayesian Learning (PCA-SBL) scheme is presented that estimates the process signal across the entire WSN field (including both active and sleeping SNs). The PCA-based transformation matrix gives a sparse representation to the process signal, while the SBL uses an approximate overcomplete dictionary to estimate it.

Subsequently, to circumvent energy and communication overheads and scalability issues associated with the centralized setting, an adaptive edge computing framework and its variants are proposed. These decouple the centralized problem into multiple sub-problems, each solvable at an edge node elected as head of a coverage region containing a set of SNs. Further, the proposed approach maintains energy balance among the SNs to avoid outage of network coverage. To limit the accumulation of estimation error in the sensor selection and estimation tasks, a retraining logic is designed.

Further, the energy efficiency aspect is looked upon for sensing multiple processes simultaneously (i.e., multi-sensing (MS)). An adaptive MS framework for a network of densely deployed solar energy harvesting wireless nodes is presented. Each node is mounted with heterogeneous sensors to sense multiple cross-correlated slowly-varying parameters/signals. To further increase the energy efficiency, network and node-level

collaborations-based MS strategies- MS-SP and MS-CC are proposed, which uses spatial proximity (SP) of nodes and cross-correlation (CC) among parameters to further prune the active sensors sets. Further, a multi-sensor data fusion technique is presented for jointly estimating all the parameters across the field nodes using under-sampled measurements sensed by MS-CC based active sensors. For this ill-posed estimation scenario, double sparsity due to spatial and cross-correlation among measurements is used to derive a PCA-based Kronecker sparsifying basis, and the SBL framework is then used for joint sparse estimation.

The last part of the dissertation proposes an energy-efficient framework for multi-step ahead sensing (i.e., taking sensing decisions for multiple measurement cycles in advance) of a temporal process. Unlike existing schemes in the literature, the temporal variations of the monitored process are directly used in finding optimized sensing instants of a sensing window for a SN. A concept of age of sample (AoS) is introduced, and expressions for the AoS and average AoS functions are derived that capture freshness of sensed samples (or inter-sample time). To incorporate the effect of process variations, weighted AoS (WAoS) and its average functions are developed. The framework optimizes this average WAoS function and energy efficiency of the SN to select a few temporal sensing instances of a sensing window while maintaining a predefined sensing quality. To make the optimization problem solvable, an upper bound on the average WAoS is derived and used. Using the few sensed measurements, the process signal across the entire sensing window is estimated. To address the non-stationary aspect of the monitored process, the length of the sensing window is adapted according to the changing correlation of the process.

The energy efficiency and stable sensing performance of the proposed frameworks are validated using both synthetic and real data of a WSN in the simulation studies. Compared to the closest existing scheme, the proposed decentralized framework provides up to 84% higher energy efficiency (network lifetime) and improves energy balance among the SNs without impacting the sensing quality. On synthetic(real) datasets, the MS-SP and MS-CC strategies are respectively 48.2 (52.09)% and 50.30 (8.13)% more energy-efficient compared to state-of-the-art (SOTA) techniques while offering stable sensing quality. On comparison with SOTA, the AoS-based framework provides 30.1% gain in sensing quality while consuming nearly the same sensing energy. Further, it consumes 22.4% lesser sensing energy to maintain nearly the same sensing quality. Further, heat-maps of the estimated field signals of parsimoniously sensed multi-source parameters are also provided which may aid in source localization IoT applications.

सार

इंटरनेट ऑफ थिंग्स (IoT) के आगमन के साथ, IoT उपकरण द्वारा उत्पादित डेटा की मात्रा, इसके भंडारण, संचार, संगणना, सुरक्षा, मापनीयता, और सिस्टम की ऊर्जा स्थिरता पर गंभीर चुनौतियां पेश करता है। इन्हीं चुनौतियों के समाधान के लिए यह शोध प्रबंध वायरलेस सेंसर नेटवर्क (WSN)-सहायक आईओटी अनुप्रयोग के नोडलेवल और नेटवर्क-स्तर पर ऊर्जा-कुशल अनुकूलित संवेदन के लिए ढांचा प्रदान करता है। निगरानी प्रक्रिया में निहित सहसंबंध विरल/पारदर्शी प्रदर्शन करने की अनुमति देता है संवेदन गुणवत्ता से समझौता किए बिना संवेदन, जिससे ऊर्जा की बचत होती है। इसके अलावा, ये अंडर-सैंपल माप का उपयोग प्रक्रिया संकेत का अनुमान लगाने और पूरे WSN क्षेत्र के हीट-मैप को उत्पन्न करने के लिए किया जाता है।

शोध प्रबंध के पहले भाग में, एक स्थानिक-अस्थायी प्रक्रिया की निगरानी के लिए सघन रूप से तैनात WSN के स्थायित्व में सुधार के लिए एक उपन्यास केंद्रीकृत अनुकूली सेंसर चयन ढांचा विकसित किया गया है। प्रक्रिया में निहित सहसंबंध के कारण, WSN की संवेदन गुणवत्ता और ऊर्जा दक्षता को संयुक्त रूप से अनुकूलित करके चयनित कुछ सेंसर नोड्स (SNs) को चालू/सक्रिय करने का विचार प्रस्तावित है। अंतर्निहित प्रक्रिया की अनुमानित विविधताओं के अनुसार सक्रिय एसएन के आकार को अनुकूलित करने के लिए एक प्रतिक्रिया तंत्र विकसित किया गया है। इसके अलावा, एक संयुक्त प्रिंसिपल कंपोनेंट एनालिसिस-स्पैर्स बायेसियन लर्निंग (पीसीए-एसबीएल) योजना प्रस्तुत की गई है जो पूरे डब्ल्यूएसएन फील्ड (सक्रिय और स्लीपिंग एसएन दोनों सहित) में प्रोसेस सिग्नल का अनुमान लगाती है। पीसीए-आधारित परिवर्तन मैट्रिक्स प्रक्रिया संकेत को एक विरल प्रतिनिधित्व देता है, जबकि एसबीएल इसका अनुमान लगाने के लिए एक अनुमानित पूर्ण शब्दकोश का उपयोग करता है।

इसके बाद, केंद्रीकृत सेटिंग से जुड़े ऊर्जा और संचार ओवरहेड्स और स्केलेबिलिटी मुद्दों को रोकने के लिए, एक अनुकूली एज कंप्यूटिंग फ्रेमवर्क और इसके वेरिएंट प्रस्तावित हैं। ये केंद्रीकृत समस्या को कई उप-समस्याओं में विभाजित करते हैं, प्रत्येक को एसएन के एक सेट वाले कवरेज क्षेत्र के प्रमुख के रूप में चुने गए किनारे के नोड पर हल किया जा सकता है। इसके अलावा, प्रस्तावित दृष्टिकोण नेटवर्क कवरेज के आउटेज से बचने के लिए एसएन के बीच ऊर्जा संतुलन बनाए रखता है। सेंसर चयन और आकलन कार्यों में अनुमान त्रुटि के संचय को सीमित करने के लिए, एक पुनर्प्रशिक्षण तर्क तैयार किया गया है।

इसके अलावा, ऊर्जा दक्षता पहलू को एक साथ कई प्रक्रियाओं (यानी, मल्टी-सेंसिंग (एमएस)) को समझने के लिए देखा जाता है। घनी रूप से तैनात सौर ऊर्जा संचयन वायरलेस नोड्स के नेटवर्क के लिए एक अनुकूली एमएस ढांचा प्रस्तुत किया गया है। प्रत्येक नोड को कई क्रॉस-सहसंबद्ध धीरे-धीरे-भिन्न मापदंडों/संकेतों को समझने के लिए विषम सेंसर के साथ रखा गया है। ऊर्जा दक्षता को और बढ़ाने के लिए, नेटवर्क और नोड-स्तरीय सहयोग-आधारित एमएस रणनीतियाँ- MS-SP और MS-CC प्रस्तावित हैं, जो आगे की छंटाई के लिए मापदंडों के बीच

नोड्स और क्रॉस-सहसंबंध (CC) की स्थानिक निकटता (SP) का उपयोग करती हैं। सक्रिय सेंसर सेट। इसके अलावा, एक मल्टी-सेंसर डेटा फ्यूजन तकनीक को अंडर-सैंपल माप का उपयोग करके फील्ड नोड्स में सभी मापदंडों का संयुक्त रूप से आकलन करने के लिए प्रस्तुत किया गया है। एमएस-सीसी आधारित सक्रिय सेंसर द्वारा महसूस किया गया। इस गलत अनुमान के परिदृश्य के लिए, माप के बीच स्थानिक और क्रॉस-सहसंबंध के कारण डबल विरलता का उपयोग पीसीए-आधारित क्रोनकर स्पार्सिफाइंग आधार प्राप्त करने के लिए किया जाता है, और एसबीएल ढांचे का उपयोग संयुक्त विरल आकलन के लिए किया जाता है।

शोध प्रबंध का अंतिम भाग एक अस्थायी प्रक्रिया के बहु-चरण आगे संवेदन (यानी, पहले से कई माप चक्रों के लिए संवेदन निर्णय लेना) के लिए एक ऊर्जा-कुशल ढांचे का प्रस्ताव करता है। साहित्य में मौजूदा योजनाओं के विपरीत, एसएन के लिए एक सेंसिंग विंडो के अनुकूलित सेंसिंग इंस्टेंट को खोजने में निगरानी प्रक्रिया के अस्थायी बदलाव सीधे उपयोग किए जाते हैं। नमूने की आयु (एओएस) की एक अवधारणा पेश की गई है, और एओएस और औसत एओएस कार्यों के लिए अभिव्यक्तियां प्राप्त की जाती हैं जो संवेदी नमूनों (या अंतर-नमूना समय) की ताजगी को पकड़ती हैं। प्रक्रिया भिन्नताओं के प्रभाव को शामिल करने के लिए, भारित AoS (WAoS) और इसके औसत कार्य विकसित किए जाते हैं। ढांचा इस औसत WAoS फ़ंक्शन और एसएन की ऊर्जा दक्षता को एक पूर्वनिर्धारित संवेदन गुणवत्ता बनाए रखते हुए एक संवेदन विंडो के कुछ अस्थायी संवेदन उदाहरणों का चयन करने के लिए अनुकूलित करता है। अनुकूलन समस्या को हल करने योग्य बनाने के लिए, औसत WAoS पर एक ऊपरी सीमा व्युत्पन्न और उपयोग की जाती है। कुछ संवेदी मापों का उपयोग करते हुए, संपूर्ण संवेदन विंडो में प्रक्रिया संकेत का अनुमान लगाया जाता है। निगरानी प्रक्रिया के गैर-स्थिर पहलू को संबोधित करने के लिए, सेंसिंग विंडो की लंबाई प्रक्रिया के बदलते सहसंबंध के अनुसार अनुकूलित की जाती है।

सिमुलेशन अध्ययन में WSN के सिंथेटिक और वास्तविक डेटा दोनों का उपयोग करके प्रस्तावित ढांचे की ऊर्जा दक्षता और स्थिर संवेदन प्रदर्शन को मान्य किया गया है। निकटतम मौजूदा योजना की तुलना में, प्रस्तावित विकेंद्रीकृत ढांचा ८४% तक उच्च ऊर्जा दक्षता (नेटवर्क जीवनकाल) प्रदान करता है और संवेदन गुणवत्ता को प्रभावित किए बिना एसएन के बीच ऊर्जा संतुलन में सुधार करता है। सिंथेटिक (वास्तविक) डेटासेट पर, एमएस-एसपी और एमएस-सीसी रणनीतियां क्रमशः 48.2 (52.09)% और 50.30 (8.13)% अधिक ऊर्जा-कुशल हैं, जो अत्याधुनिक (SOTA) तकनीकों की तुलना में स्थिर सेंसिंग प्रदान करती हैं। गुणवत्ता। SOTA के साथ तुलना करने पर, AoS- आधारित ढांचा लगभग समान संवेदन ऊर्जा की खपत करते हुए संवेदन गुणवत्ता में 30.1% लाभ प्रदान करता है। इसके अलावा, यह लगभग समान संवेदन गुणवत्ता बनाए रखने के लिए 22.4% कम संवेदन ऊर्जा की खपत करता है। इसके अलावा, पारसीमोनीली सेंसड मल्टी-सोर्स पैरामीटर्स के अनुमानित फील्ड सिग्नल के हीटमैप्स हैं यह भी प्रदान किया गया है जो स्रोत स्थानीयकरण IoT अनुप्रयोगों में सहायता कर सकता है।

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List of Symbols

$\mathbf{a} \in \mathbb{R}^{N \times 1}$	A real vector of size $N \times 1$
$\mathbf{A} \in \mathbb{R}^{M \times N}$	A real-valued matrix of size $M \times N$
$\mathbf{0}_{M \times N}$	$M \times N$ matrix of zeros
$\mathbf{I}_N$	$N \times N$ identity matrix
$\mathbf{A}(m, n)$	$(m, n)^{th}$ element of the matrix $\mathbf{A}$
$\mathbf{A}(m, :)$	m^{th} row of the matrix $\mathbf{A}$
$\text{Tr}\{\mathbf{A}\}$	Trace of the matrix $\mathbf{A}$
$a(m)$	m^{th} element of the vector $\mathbf{a}$
$\ \mathbf{a}\ $	The standard l_2 -norm of the vector $\mathbf{a}$
$\mathbf{A} \in \mathbb{S}^N$	Symmetric matrix $\mathbf{A}$ of size $N \times N$
$\mathbf{A} \in \mathbb{S}_{++}^N$	Symmetric positive definite matrix $\mathbf{A}$ of size $N \times N$
$(\cdot)^T$	The transpose of the vector/matrix
$\text{diag}(\cdot)$	The standard diagonalization operation on a vector
$ \cdot $	The cardinality operation
$\cup$	The set union operation
$\text{dom } f$	Domain of the function f

List of Abbreviations

AoS	Age of Sample
BCRB	Bayesian Cramér-Rao Bound
BWU	Bandwidth Utilization
CC	Cross-Correlation
CH	Cluster Head
CS	Compressed Sensing
CPU	Central Processing Unit
DFT	Discrete Fourier Transform
EH	Energy Harvesting
EM	Expectation Maximization
FC	Fusion Center
FIM	Fisher Information Matrix
IID	Independent and Identically Distributed
IoT	Internet of Things
MS	Multi-Sensing
MOP	Multi-objective Optimization Problem
MSE	Mean Squared Error
NMSE or nMSE	Normalized Mean Squared Error
nRMSE	Normalized Root Mean Squared Error
PCA	Principal Component Analysis
PCI	Partial Canonical Identity
QoS	Quality of Service

SN	Sensor Node
SP	Spatial Proximity
SBL	Sparse Bayesian Learning
SEU	Sensing Energy Utilization
WAoS	Weighted Age of Sample
WSN	Wireless Sensor Network